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Development of Lightweight Deep Learning Model for Watermelon Disease Classification; Deployable to Mobile Device

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Abstract: *Crop disease has significantly affected the production and commercialisation of watermelon fruits, causing a drop in food security, agricultural economy and rural development. Moreover, the traditional manual method of disease classification is time consuming and not completely efficient for large scale farming. A significant means to solving this crop disease wchallenges is the use of deep learning models like VGG16 architectures. Despite their high accuracy level, they are computationally demanding and not appropriate to address the challenge of watermelon disease classification within a resource constrained environment. Consequently, a comprehensive review of related literatures was conducted and the research gaps identified, led to the development of a lightweight model for watermelon diseases classification deployable to android mobile device to support real time decision-making on farm field. It utilises the transfer learning approach with MobileNetV2, a lightweight convolutional neural network (CNN) architecture renowned for striking a balance between high accuracy and computational requirements. The dataset comprises of high-quality images of different disease classes of watermelon namely, Anthracnose, Downy Mildew, Mosaic Virus and Healthy class. Exploratory data analysis (EDA) conducted on the dataset revealed the class distribution and imbalance which facilitated the use of augmentation to increase data diversity and generalisation.The model development was carried out following the agile framework and software development life cycle (SDLC) which divided the processes into structured iterative sprints ranging from requirement analysis to model deployment and testing on android device. The model training was achieved in two phases, Feature extraction of ImageNet - MobileNetV2 pretrained weights and fine tune of the last 100 layers of the CNN architecture. The effect of batch sizes (16, 32, and 64) on the model accuracy was examined during model development and batch size of 16 performed best in terms of efficiency and generalisation with a validation accuracy of 99%.The model deployment capacity was evaluated with a different test data curated from extension service website. The TensorFlow lite version of the developed model had a size of 9.08MB while the total inference speed on 27 images of Anthracnose class and training time was 0.23 and 10634.26 seconds respectively with an overall classification accuracy of 56% on model developing platform and 61% on developed mobile application built with Kotlin and Jetpack Compose. The test evaluation identified anthracnose disease to have a higher classification accuracy which is probably due to the unique nature of the training set.Broader legal, social, and ethical issues were also noted in the study, such as the ethical application* *of Artificial Intelligence (AI), adherence to the UK GDPR, and fair access to digital tools for small holder farmers.This research successfully demonstrated the feasibility and effectiveness of the developed lightweight deep learning model through the performance results which showed its capacity in classifying watermelon diseases within limited resources like mobile devices when compared to heavyweight models like VGG16. This becomes significant for AI solution for disease management in a low resource environment for sustainable agriculture. Future research could focus on enhancing model interpretability, increasing robustness and generalisability of the model through expansion and integration of realistic field data during model training and diversification of model test on different low resource devices.*

Keywords: watermelon, crop disease, anthracnose, mosaic virus, downy mildew, sustainable agriculture, artificial intelligence, deep learning, image classification, CNN, mobilenetv2, transfer learning, data augmentation, feature extraction, model optimization, accuracy, tensorflow, real-time prediction, android deployment, edge computing.

INTRODUCTION

Agriculture is a backbone to ensure food security, economic strength, and a global source of livelihood, specifically in developing nations where a greater portion of their economy is highly dependent on agriculture (FAO, 2021). Crop diseases have substantially affected agricultural production of watermelon, leading to a severe threat to worldwide food security and destabilisation of farmers ‘income (Fenu and Malloci, 2021). Early and accurate identification of crop diseases is necessary to prevent further damage, reduce intending losses and increase crop yields (Singh et al., 2020; Bagga & Goyal, 2023). Recent development in artificial intelligence (AI) and image processing have transformed various sectors, such as agriculture, by creating innovative technologies to improve decision-making processes and management of resources (Singh et al., 2020). Machine deep learning especially Convolutional Neural Networks (CNNs), has evolved as an effective method for disease identification and classification in agricultural environment, demonstrating a significant improvement over traditional means of image processing (Mohanty et al., 2016; Chen et al., 2020).

Despite these improvements, deploying AI models in real-world agricultural environments experiences some serious challenges such as computing resources and model complexity. Farmers often operate in resource-constrained environments with limited opportunity to assess high-performance computing infrastructure. Thus, developing lightweight and efficient deep learning models specific for mobile or edge devices deployment remains crucial for effective real-time disease classification in agricultural environment (Qian et al., 2021).

Problem Domain

Watermelon (*Citrullus lanatus*) is a fruit cultivated globally for its nutritional and commercial significance (Masih and Kaur, 2021). It is a nutrient-dense fruit high in lycopene, vitamins A, B6, C, carotenoids, and antioxidants that can lower blood pressure, cholesterol, cancer, and obesity, among other health problems (Nadeem et al., 2022). It is useful for food colouring and nutrition because it has more lycopene than tomatoes. In Africa, it promotes food security through nutrition, economy through rural development, and land conservation as a fruit that is widely accessible and reasonably priced (Dube, Ddamulira and Maphosa, 2020).

The evidence of its economic importance is seen in Europe, where high demand of the product is experienced during the spring and summer seasons. Despite the increased watermelon prdfoduction in Spain between 2014 and 2023 which is approximately 1.38million tons (Trenda, 2024), it is recorded that there was 16% increase in importation of watermelon between 2018 and 2023 to meet up with the demand indicating its acceptance and importance (Paqui and Peperkamp, 2024). Its economic importance is seen in watermelon production in Spain with a record of 31.23% increase in sales in 2023 (FreshPlaza.com, 2024).

However, watermelon diseases, such as anthracnose, downy Mildew, mosaic virus, and leaf spot diseases are mostly predominant in watermelon which account for over 50% production loss thereby reducing its yield and quality if not promptly managed (Ismail & Sulaiman, 2021; He et al., 2021). Identification of crop disease has been performed by professionals through traditional means such as visual inspection of leaves or fruits. Over the year, this method has seen some improvements. However, it is time consuming, labour demanding and not ideal for large scale farm operations leading to delayed intervention, and increased severity of the disease and possible losses (Kotwal, Kashyap and Pathan, 2023).

CNN-based models, such as MobileNetV2, have been explored in recent research for general image classification tasks because of its efficiency and suitability for mobile device deployment (Kaur et al., 2023). However, little research has been done on how model hyper parameters affect model performance and application of these lightweight models for agricultural disease classification, especially watermelons diseases. The focus is not only to achieve a higher accuracy but to consider low computational requirement thereby making the model deployable to edge or mobile devices for agricultural fields (Jayakumar et al., 2020; Banerjee et al., 2023).

Aim and Objectives

The main aim of this study is to develop and evaluate a MobileNetV2-based deep learning model that is reliable, deployable, and lightweight for watermelon disease classification on mobile or edge computing devices with limited resources. This model will be utilised in classifying the four selected diseases affecting watermelon on mobile devices which will improve its production through quick detection and intervention.

The following objectives are considered for this study:

- Literature review on watermelon disease classification and lightweight models, critically reviewing the methodologies, techniques and models as well as their applications and results.
- Exploratory Data Analysis (EDA) on the watermelon disease image dataset to analyse the features, class distribution, and other factors that can affect the proposed model performance.
- Develop and implement a lightweight deep learning model for watermelon disease classification on mobile devices using MobileNetV2 transfer learning technique.
- Evaluation of model adaptability and performance when deployed on resource constraint computing devices like an android mobile phone.

- Analyse the obtained results and observations in relation to another state-of-the-art techniques while identifying the strengths and challenges when used in real world.
- Evaluate the legal, social, ethical and environmental consideration in deploying crop disease classification model in agricultural settings.

Research Questions

This research is guided by these questions

- RQ1: Can watermelon disease classification be performed with high accuracy by a lightweight CNN model, MobileNet V2 in comparison to the heavyweight model?
- RQ2: Does the input batch size during model training affect the accuracy level and performance?
- RQ3: How possible can the developed model be deployed to a mobile device without effect on the performance?
- RQ4: Is there any legal, social and ethical consideration for deploying AI models in agricultural settings?

METHODOLOGY

To achieve these objectives in line with the research questions, a systematic and well structure methodology was employed using agile software development framework comprising of detailed literature review on existing research to identify gaps, followed by exploratory image data analysis of the watermelon disease dataset to uncover trends, assess image quality and Red-Green-Blue colour evaluation. The next phase was the use of transfer learning technique in the model design implementation which was carried out with a Convolutional Neural Network (CNN) architecture, MobileNetV2 because of its lightweight optimised ability that strikes a balance between model accuracy, performance and adaptability on resource constraint computing devices (Shahi et al., 2022). The transfer learning technique was employed using the ImageNet-pretrained weights for transfer of existing features into the new domain through feature extraction for improved performance and generalisation (Antwi et al., 2024). The model training was structured in two phases. The feature extraction and fine-tuning stage. Each phase consisted of various modifications and hyper parameter tuning to achieve an impressive performance (Carvalho et al., 2021). Experiment was conducted during the model development stage to assess the effect of hyper parameter tuning such as batch size to the performance level. The experiment was followed by evaluation of the selected model using performance metrics like overall accuracy, precision, recall value, F1 score in collaboration with confusion metrics. The developed model was converted into TensorFlow lite for deployment to android device where evaluation was carried out to assess the performance level on resource constraint computing devices and validate its real-world application.

Achieved Outcomes

The outcome of the research work includes

- A detailed understanding of the various CNN based models, strengths and weaknesses as applied to disease classification of crops.
- An insightful analysis of the watermelon disease dataset and disparity mitigation using augmentation techniques.

- A developed lightweight MobileNetV2 deep learning-based model for watermelon disease classification with 99% validation accuracy and validation of its real-world application with realistic images on developed demo android application with 61% accuracy.
- Proper insights in the performance metrics and adaptability of the model when deployed in resource constrained agricultural production environment.
- Evaluation and validation of the model performance when deployed on android mobile devices indicating its ability to perform real time and offline watermelon disease classification.
- Recommendation for further studies and research in the real time crop disease classification domain like watermelon such as dataset expansion and increase in diverse testing on multiple devices.

Structure of the report

This report is organized in seven chapters, with each chapter addressing a specific aspect of the research project. The organisation is such that it proceeds in a logical order from background and aim of the study, through design and fieldwork, to final assessment and conclusion.

Chapter one is the introduction which presents the background and setting of the research, formulates the problem statement, defines the research aim and objectives, outlines the research questions, presents the methodology and expected outcomes, as well as introducing the structure of the entire report. Chapter Two is the Literature Review which discusses existing work concerning image-based crop disease detection, deep learning in agriculture, and implementation of MobileNetV2. It critically reviews such existing research, highlights gaps in literature, and places the research in focus over the larger body of research works. Chapter three provides the Methodology to describe the research design, Agile implementation and methodology adopted in this work, dataset analysis, augmentation strategies, training configuration and model evaluation. It rationalizes why MobileNetV2 is used, outlines how data is acquired and pre-processed, and presents experimental setup such as augmentation, training setup, and evaluation. Chapter four is the discussion of the implementation and testing of the model with Python, TensorFlow, and Keras. It covers training setup, environment setup, test procedure (both functional and acceptance test), and Android implementation for performance benchmark. Chapter five provides the Evaluation report where a thorough analysis of the model's performance through comparison with other models, training/validation graphs, confusion matrices, and classification metrics. It comprises a critical assessment of the model's precision, constraints, and possibilities for practical implementation. Chapter six is the Discussion of the project experiments. It provides a thorough analysis of the results, talks about the extent at which the goals of the study were realised, evaluates the outlined methodology's advantages and disadvantages, looks at ethical and legal issues, and suggests future research directions in the research domain. Chapter seven is the last chapter which provides the summary of the research procedures and results. The project results are outlined, knowledge contributions are highlighted, challenges are noted, and recommendation for additional research and development were made.

LITERATURE REVIEW

This chapter critically examines existing literature on convolutional neural networks (CNNs) based deep learning methods for classifying watermelon disease with emphasis on lightweight model development and application.

The objective is to identify the technological progress made and research gaps in optimum deployment and use of watermelon disease classification model for real time results on low resource computing devices which lays a foundation for justification of lightweight MobileNetV2 deep learning model usage.

Crop Disease Detection and Classification Using Image Processing

Crop diseases have a major effect on income stability of farmers, food security, and agricultural production. In the study of the European watermelon market by Paqui and Peperkamp (2024), emphasis was made on the significance of disease-free crops for export sustainability. Recently, the survey conducted in Bangladesh identified that increase in diseases affected watermelon production and noted that watermelon crop is seriously at risk due to these findings (Ferdous, 2024). Traditional methods of disease classification have been dependent on visual evaluation by agricultural specialists which has shown to be ineffective, sensitive to subjective errors, and time-consuming for large-scale farms (Damicone & Brandenberger, 2020).

In recent time, the use of digital images and computational algorithms with automated image processing techniques have gradually replaced human manual approach for the accurate and rapid detection and classification of crop diseases (Ferentinos, 2018). The methodological shift from manual to deep learning for crop disease classification was examined by Kotwal et al. (2023), highlighting the necessity of robust and scalable models.

The use of CNN based deep learning technique has recently transformed image-based plant disease identification (Upadhyay et al., 2025). It has shown it supremacy in accurate crop disease classification when compared to the traditional methods because of its ability to extract relevant features from raw image data (Vishnoi et al., 2020). Although RNN has demonstrated some higher accuracy when combined with k-means clustering on watermelon disease classification, its complex structure and high computational requirements creates a setback as an alternative to CNN models application to agriculture (Jayakumar et al.,2020).

Despite these improvements, many CNN based models still face the challenge of high computational resources requirement creating a barrier to practical deployment to low resource agricultural environment (Kotwal et al., 2023).

Deep Learning Techniques for Crop Disease Detection

CNN and transfer learning architectures, including AlexNet, ResNet, VGG-16, and MobileNet, have gained popularity in agricultural applications because of their comparative easy implementation and robust performance when deployed (Narvekar & Rao, 2020; Wang & Wu, 2023). Khannum, R and Y (2024) applied VGG16 for automatic detection of downy mildew disease of watermelon which resulted

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to a high accuracy of 100% with minimal loss. Despite its huge performance, it lacks the computational requirement for mobile deployment which is a gap needed to cover in this research.

Transfer learning approach has also been applied to developing new models (Upadhyay et al.,2025). It is a machine learning technique where a model created for one task is used as a foundation for another model development by utilising the knowledge from the first task to enhance learning effectiveness and performance on the new task (Zhuang et al., 2021). This approach saves the required time and computational power for training a new model for a new task by replacing the final network layers to increase a convolutional neural network's efficiency and efficacy (Mehrotra et al., 2020). Transfer learning reduces computing power needed to train a model with CNN from the beginning. The pretrained model utilises the weights already established with imageNet which its effectiveness has been established (Hosna et al., 2022)

Likewise, transfer learning using a renowned lightweight architecture, MobileNetV2, has been efficiently applied in fruit and vegetable classification tasks, validating its potential for mobile deployment (Gulzar, 2023; Shahi et al., 2022). These and many more developed models and techniques have influenced artificial intelligence (AI) in Agriculture and has become a strong driver for the sector.

MobileNetV2 for Lightweight Watermelon Disease Classification

MobileNet V2 is a low-latency, lightweight convolutional neural network architecture that balance accuracy and computational expense for effective image classification on resource-constrained devices such as mobile phones or embedded systems. It makes use of two hyper-parameters and depth wise separable convolutions with customised latency and size limits, unlike other models which makes it a perfect model for monitoring systems, picture categorisation, augmented reality applications and real time crop disease classification like watermelon where accuracy and model complexity are considered (Dong et al., 2020).

The inverted residuals, linear bottlenecks and the depthwise separable convolution makeup the MobileNetV2 architecture. (Liu et al., 2023). The linear bottleneck and residual features help to reduce the number of convolutional calculations whereas depth wise separable convolution feature enables feature reuse and fewer parameters to prevent information loss which is effective for computer vision task unlike its previous version that has limited depth with lack of residual connections (Gulzar, 2023; Shikdar et al., 2024).

Although MobileNetV3 is considered for higher accuracy in some tasks, it creates difficulty in fine-tuning for domain-specific problems without extensive annotated datasets because of its sophisticated architecture and hyperparameter sensitivity (Alhazmi, 2023). When it comes to small-to-mid-sized agricultural datasets, MobileNetV2 offers a better balance of performance, customisation, and accessibility. Figure 2.1 shows the structure of MobileNetV2 architecture.

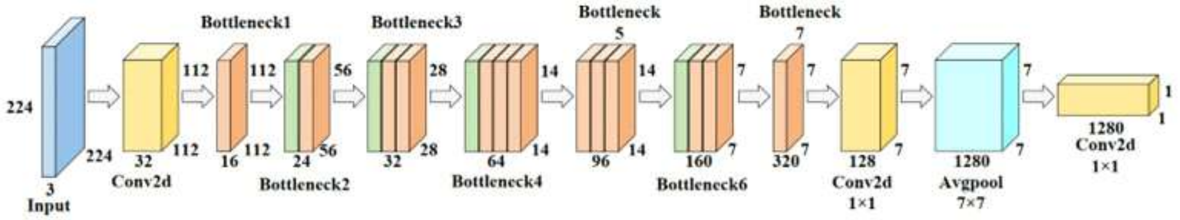

Figure 2.1: MobileNet V2 Network Structure (Liu et al., 2023)

Each of the linear bottleneck blocks contains a 1x1 pointwise convolution (expansion layer) that uses an expansion factor to increase the dimensionality of the input tensor, a 3x3 depthwise convolution that maintains efficiency through application of spatial filter to each input channel and then a projection layer that preserved useful feature which has a 1x1 pointwise convolution for dimensionality reduction. MobileNetV2 structure enables effective spatial filtering, where output features are compressed to reduce computing requirement prior to extension into the feature space to learn richer representation. This makes mobileNetV2 a better option for balance between classification accuracy and computational complexity (Moyazzoma et al., 2021).

MobileNetV2 Application in Agricultural Disease Classification

MobileNet V2 Architecture has been used in various research works to classify different agricultural crop diseases, demonstrating its adaptability and effectiveness in operation. Moyazzoma et al. (2021) applied MobileNetV2 in the identification of diseases for five different crops which demonstrated the superior performance and widespread use of the architecture at a reduced computational requirement when compared to other traditional models. However, its implementation to various task has varied due to model configurations, data handling and optimisation of hyper parameters (Carvalho *et al*., 2021). A major research gap is identified by the fact that many current systems lack rigorous optimisation strategy specific to watermelon diseases (Banerjee *et al*., 2023).

Precision agriculture is transforming rapidly due to the integration of Internet of Things (IOT) and AI which has been proven by recent studies conducted on the use of lightweight deep learning models for real time disease classification and detection (Issa *et al*., 2024). These methods reduce latency and dependency on cloud computing for crop image processing when it is deployed on a device for offline performance. Guan et al. (2023) demonstrated real-time classification capacity of MobileNetV2 by creating an efficient plant disease detection model specific for edge deployment. Similar method can also be applied to watermelon disease classification.

Current Research on Watermelon Disease Classification

Research on watermelon disease classification using CNN-Based model is very much limited when compared to research in other cash crops. Recent studies have demonstrated encouraging results, but they are mostly of high computational architectures or falling short in completely addressing deployment constraints in the real-world application (Jayakumar et al., 2020; Shikdar et al., 2024).
For instance, a hybrid CNN and SVM model was proposed by Banerjee et al. (2023) which achieved high classification accuracy but at a significant computational cost, which made it less appropriate for use on edge devices with limited resources.

Additionally, Alhazmi (2023) proposed optimised CNN model for categorisation of various stages of watermelon diseases. However, there was less analysis of the development in terms of model size, inference speed and real time assessment when deployed on mobile devices. Likewise, Arora et al. (2024) and He et al. (2020) applied deep learning models to identify watermelon diseases with focus on only the model accuracy but less emphasis on assessing possible lightweight requirements and deployments.

Gaps in Existing Literature

In the literature review so far, some notable gaps have been identified in terms of model optimisation and deployment of lightweight models for general crop disease classification within low resource environment as a consideration.

Most developed models have high accuracy rate but ignore significant factors such as model size, latency, computing cost, and adaptability for usage in mobile or edge deployment (Bi et al., 2022). Considering the low infrastructure in agricultural setting, these constraints make it impracticable to employ precise models in real-world applications.

In the use of CNN baseline model for corn disease classification, Saeed et al. (2021) achieved an accuracy of 97.81% and 97.48% with ResNet152 and InceptionV3 respectively. For improvement, a hybrid approach to crop disease classification by Kukreja, Sharma and Yadav (2023) combined CNN and Support Vector Machine classifier (SVM) for rice sheath disease classification by performing Binary classification of the disease presence and multiclassification of the disease severity operation. The hybrid model generated a 95.2% accuracy, demonstrating a better model more than using only CNN. In further research, the same hybrid model was used by Banerjee et al. (2023) to classify 8 disease classes of watermelon. Although it demonstrated a 70.29% precision, it did not meet up with the required computational strength for mobile deployment to aid real time usage. On rice disease classification, V et al. (2024) achieved 99.74% overall accuracy through a modification of the algorithm structure by integrating attention mechanism and advanced activation functions. This demonstrated the possibility of crop disease classification but there was no information on the computational requirement and the field-based result to justify it in real world application.

Higher computational requirement still limits the detection of watermelon diseases in a natural environment despite the 924% accuracy achieved by He et al. (2020) in the pre-selector setting formula of the single shot multibox detector model.In general plant classification work by Alhazmi (2023), a CNN architecture, VGG16 was used as the based model while the weights and the optimisers were modified. This delivered 94% recall value. The use of multiple plants for this task creates deployment barrier since every crop disease is unique and deployment to low resources device is not attenable. The same challenge faces the binary type of watermelon disease classification model developed by Khannum, R and Y (2024) despite its great 100% accuracy value.

The possibility of overfitting and risk of narrow application of the model was observed in the developed deep learning model by Ferentinos (2018) during development of a plant disease detection and diagnosis model despite the 99 percent accuracy. In the review conducted bySharma (2024) for deep learning for plant disease detection, different approaches, techniques and transfer learning were utilised, and improvement was identified. However, the result has narrow domain usage, with complex model that increases training and inference time. It is worth knowing that limited access to realistic data remained a challenge in building deployable models.

Furthermore, many existing classification or detection models are developed with augmented or balanced datasets which rarely undergoes validation under real-world conditions. This is a limitation which reduces the robustness and generalisation of the model. As Antwi et al. (2024) explained, data augmentation alone does not depict the true representation of the object in real world condition which leads to poor model performance result. Therefore, there is need for a robust lightweight CNNs that can be reliable in real-world scenarios while striking a balance between accuracy and computational efficiency. Table 2.1 shows the summary of the previous works done with deep learning approach for crop disease detection and classification.

This research aims to close these gaps by utilising MobileNetV2, an architecture designed for mobile environment, and by combining performance benchmarking, variation in batch-size, and real-world testing methods. The challenges of creating a scalable, accurate, and lightweight deep learning model for the classification of watermelon diseases is addressed in this study through combination of technical approach and mobile device deployment considerations.

Table 2.1: Summary of deep learning application on crop disease classification

Study	Technology/Algorithm used	Dataset used	Project Task	Selected crop	Performance Evaluation	Limitation
Khannum, R and Y (2024)	VGG-16 CNN model	Watermelon image data	downy mildew disease detection	Watermelon	100%	Image detection of one type of disease and high computational requirement.
Wang, Wang and	MobileNet + Attention Mechanism	Rice image data	Rice disease	Rice	94.65%	High Computatio

Peng (2021)			classification			nal requirement
V et al. (2024)	CNN hybrid	Rice image data	Rice disease Classification	Rice	99.74%	Increased training and inference time
Hamid et al. (2025)	VGG16, MobileNetV2, Xception, ResNet	Multi Crop image Data	Model comparison on Multi crop disease classification	Multi Crop	99%	High Computational requirement with VGG16
Study	**Technology/Algorithm used**	**Dataset used**	**Project Task**	**Selected crop**	**Performance Evaluation**	**Limitation**
He et al. (2020)	Single shot multibox detector model	Watermelon leaves image data	Disease detection in watermelon	Watermelon	92.4%	High Computational requirement
Jayakumar et al. (2020)	K-means clustering and stacked RNN	Watermelon image	Disease classification of watermelon	Watermelon		High processing requirement
Kaur et al. (2023)	MobileNetV2	Multi crop dataset	fruit and vegetable	Multi crop	96%	Not disease classification

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			classification			
Chavan and Shirdhonkar (2024)	MobileNetV2, InceptionV3, and ResNet50	Cotton image	Cotton crop disease diagnosis	cotton	93%	Not specific to watermelon
(Banerjee et al., 2023)	CNN-SVM model	Watermelon	Watermelon Multi disease classification	Watermelon	93%	Not lightweight model

Ethical, Social, and Environmental Considerations

Legal Implication

Data ownership in AI projects is a concern because farmers who owns the images might lose the image right to businesses or organisations if there is no authorisation (Uddin, Chowdhury and Kabir, 2024). Consequently, relevant permissions should be granted to adhere to privacy and data protection laws of the deployment region. Also, model biases can lead to litigation. Therefore, question is raised on who is held responsible for any fault in the developed system which could lead to crop loss (Dara, Hazrati Fard and Kaur, 2022). This challenge can affect finance and the environment.

Social Implications

AI technology requires enabled devices such as smartphones and internet connections which are not easily available to small scale farmers in underdeveloped nations (Cutlip, 2022). To address the inequality in technology usage, AI tools should consider the underrepresented potential users during design phase for inclusiveness to achieve its purpose. AI tool is meant to assist professionals in their task. A solution-based project in agriculture should be an advisory tool and should not cause fear of loss of job which can affect economic stability in rural environment that relies on traditional farming methods (Ryan, 2023). The approach is to incorporate the disease classification device into the working tools of the farmers for easy adaptation to AI in agriculture. The issue of trust in the system remains a challenge for adoption of AI in agriculture because of lack of explainability which causes low acceptance. This should be considered in any AI development in agriculture.

Ethical Consideration

Bias in the Model: Various agricultural variation could lead to bias in the developed model which could affect the results (Okengwu et al., 2023). Typical considerations are climate, soil, crop varieties and stage of disease. These should be considered during implementation of disease classification models in agriculture. Environmental concerns: Disease misclassification from AI models may result in the unnecessary application of disease control measures like pesticides thereby degrading soil and contaminating water (Okengwu et al., 2023). Therefore, the developed model should keep the environment safe from environmental contamination due to wrong result.

The collected image data will be exclusively used for study purposes and required permissions have been considered to safeguard the confidentiality of the data. Application of AI and deep learning technology in agriculture introduces ethical, social, and environmental concerns. Precision agriculture driven by AI significantly increases sustainability and production, but there are concerns about biases in the algorithm, privacy of the data used, and the effects of massive technological infrastructure on the environment (Okengwu et al., 2023; Dara et al., 2022). To reduce any side effects and promote sustainable agricultural production, ethical standards and responsible AI practices must be considered into technology deployments (Uddin et al., 2024).

Summary

This literature review identifies the current trends and unsolved challenges in image processing and deep learning for agricultural crop disease classification, especially as regards to watermelon diseases. It is noted that MobileNetV2 emerges as a favourable architecture for addressing resource constraints associated with on-farm deployments of disease classification applications. However, comprehensive studies evaluating lightweight models' performance specifically for watermelon disease detection and classification on devices has remained insufficient. To these identified gaps, this research projects to develop and evaluate the performance of a robust, lightweight MobileNetV2-based model suitable for real-time mobile deployment, closing the critical gaps identified in the existing related literature and significant contribution to the practical application in agriculture.

METHODOLOGY

In this chapter, the methodology for developing the watermelon disease classification model will be outlined. It includes a thorough explanation and justification of the selected methods and design choices. It explains the rationale behind employing specific methods, particularly transfer learning, exploratory data analysis (EDA), model training, and evaluation processes.

Research Approach

The study employed the agile framework for software development lifecycle (SDLC) with focus on development and evaluation of artefacts (Brocke et al., 2020). This artefact is an Android mobile device application with a deployed watermelon classification model to justify the use of optimised CNN model suitable for resource-constrained mobile and edge environments. This project approach was chosen because it explicitly supports iterative design, testing, and refinement of technological solutions in real-world environment while addressing the identified technological gap with creation of a practical model and android application. Gantt chart was used as the project management tool for managing and monitoring the project timeline and progress (Radujković and Klepo, 2021).

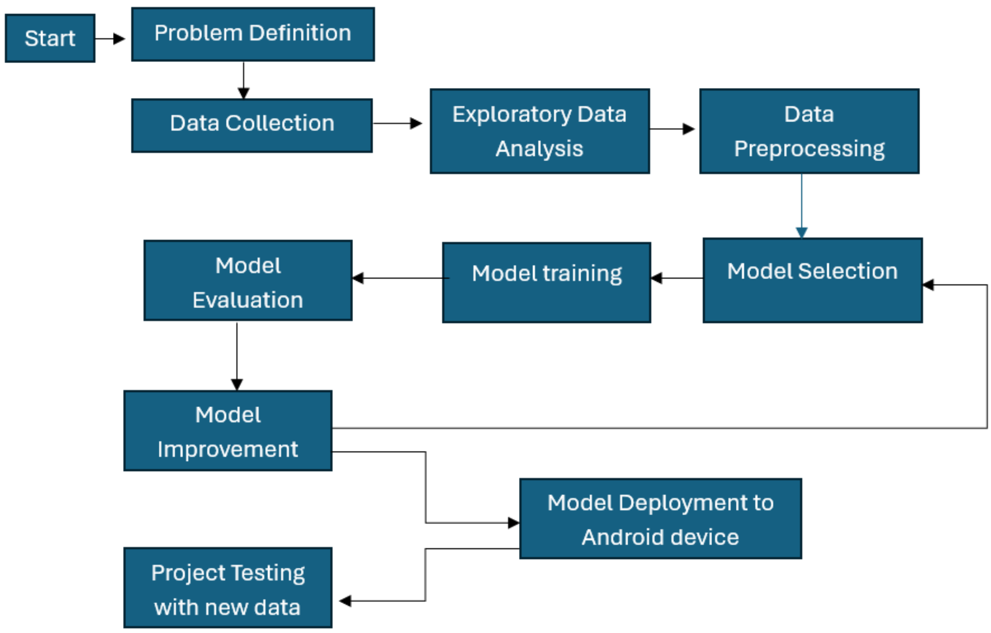

Figure 3.1: Flow chart of the process for the project development

Justification of Chosen Methodology

This study follows a systematic iterative process using the agile framework. This is because the project aligns with the principles of agile for adaptability, incremental improvement (sprints) and responsiveness to varying requirements and unforeseen challenges (Filippetto, Lima, and Barbosa, 2021). This was evident in the development, implementation, refinement and improvement of the MobileNetV2 based classification model on mobile device application by the project team.

For the mobile application design, software development lifecycle (SDLC) was employed to facilitate the management of the application development. This structured principle contains important phases namely, requirement analysis, planning, design, project implementation (coding), testing, deployment and maintenance (Jarikre et al., 2022). These phases were used during the development process together with agile framework for iterative processes and progress monitoring.

Research Procedure

These phases are categorised into specific procedures for the project actualisation which is to develop a lightweight watermelon disease classification model that can identify the type of disease found in a watermelon leaves or fruits. The design procedure is as follows

- Data collection: The four classes of the watermelon disease dataset, comprising of Anthracnose, Downy Mildew, Healthy, and Mosaic virus was obtained from an open source repository, Mendeley website
- Exploratory data analysis: A comprehensive statistical and visual analysis of the image data were performed to understand the data distribution, class imbalance and image quality.

- Data preprocessing: To prepare the dataset for training, image resizing, normalisation and data augmentation were performed.
- Model architecture selection: A pretrained model, MobileNetV2 was selected as an architecture for the watermelon disease classification model.
- Model training: The dataset was split into training and validation set. Such that 80% was used for training while 20% was used as a validation set to monitor the model performance.
- Model Evaluation: Model performance metrics were used to assess the efficiency of the disease classification model. Metrics such as accuracy, precision, F1 score, recall, and confusion matrix for each class performance assessments.
- Model Improvement: To achieve a robust classification model, some parameters were varied and modified such as learning rate, and image input batch size and number of epochs.
- Model Deployment: Evaluation of performance of the model in mobile devices were conducted by identifying the inference speed, and model size for real time applications.
- Model Test: Testing on mobile device was conducted using image data that represent the real images from field to assess the performance level of the developed model on agricultural field environment.

Data collection

The watermelon disease image dataset was obtained from a public assessable source, Mendeley Data with permission granted for right to use the dataset for personal and commercial purposes under the creative common law. The dataset contains images representing three various watermelon diseases and the healthy class. These diseases include mosaic virus, anthracnose, and Downy Mildew, each carefully annotated to facilitate the supervised learning process.

Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) was performed to gain a comprehensive understanding of the dataset prior to model development. This was to ensure data consistency, discover irregularities such as class imbalance, and assess image data quality and its variations which is very important for effective model training in computer vision task in agriculture (Fariq & Jumadi, 2020; Kurmi & Gangwar, 2021).
The major analysis includes

Dataset Overview

This section identifies number of images in each class, identification of image size, format, quality and statistical summary of the image. A bar chart was used to visualise the class distribution to identify which class dominates or underrepresented. Pie chart was also used to show the proportion of the class representation. It was essential to understand this class distribution which guides the implementation of augmentation techniques. Class imbalance has been a common challenge in agricultural deep learning task which has led to underperformed models due to bias in the system (Sharma, 2024; Joshi et al., 2024).

The image dimensions and file format of the dataset were assessed to maintain consistency and standardisation in the training process as required by the CNN models like MobileNetV2 (Talebi & Milanfar, 2021). Likewise, the image quality was checked for blur or low-resolution image for possible exclusion or modification using standard techniques that ensures robust training (Yang et al., 2022).

Image Colour Distribution
Colour distribution among the images in each class was performed to discover the relationships among the different images using colour distribution approaches. This relationship is a Red-Green-blue (RGB) histogram analysis which visualises the colour distribution across image channels. This analysis is necessary in crop pathology where variations in colour can indicate a particular type of disease symptoms (Ferentinos, 2018; Guan et al., 2023).

Visual Inspection of Image data
This is to graphically represent the data information and distribution. Some of the representations are random image views, bar charts and pie charts.
Each class of the dataset was examined manually to identify similarities and differences among them. This procedure helped to improve the model validation approach and supported the choice of augmentation approaches. Additionally, a manual review of the dataset revealed possible labelling errors or noise, which were fixed when feasible (ANTWI et al., 2024).

Data Augmentation Strategy Design

Augmentation has been recognised as an effective method to artificially expand agricultural datasets and mitigate overfitting, especially in plant disease classification tasks (Zhuang et al., 2021; Liu et al., 2023).

Based on EDA findings, a series of robust data augmentation techniques were implemented to address class imbalance, improve dataset diversity, and enhance model generalisation. These augmentation methods aimed to simulate real-world environmental variability and were selected based on established practices in agricultural deep learning research (Zhuang et al., 2021; Liu et al., 2023). Summary of the augmentation performed are in table 3.1.

- Brightness Modification: Images were randomly brightened or darkened to account for different lighting conditions typically encountered in agricultural fields. This enabled the model to recognise disease patterns under varying illumination levels, a common challenge in field-based image acquisition.
- Horizontal and Vertical Flipping: Images were flipped in both horizontal and vertical directions to increase spatial diversity. This helped the model generalise to different orientations and angles of watermelon leaves, minimising orientation bias.
- Shifting: Random horizontal and vertical shifts were applied to simulate variability in framing and leaf positioning during image acquisition. This improved the model’s translation invariance.
- Rotation: Images were randomly rotated to simulate the natural variability of leaf orientation in real-world environment. This technique was particularly useful for improving the model's ability to generalise across different field scenarios.
- Zooming: A gentle zooming effect of 0.2 was used to focus attention on both general leaf patterns, the fruit and localised lesion textures, allowing the model to detect disease development at varying scales.

- Shear Transformation: Shear was applied to distort the image along the x and y axis, simulating natural shape deformations of leaves or fruit caused by environmental factors such as wind or handling.

Table 3.1: Summary of the Augmentation techniques

Augmentation Methods	**Description**	**Purpose**
Brightness adjustment	Random increase and decrease of image brightness	Replicates the different lightening conditions in actual farm environment.
Horizontal flip	Image mirrored across its vertical axis	Creates orientation variation for spatial diversity
Shifting	Random horizontal and vertical image rendition	Simulation of differences in leaf or fruit placement and framing
Zooming	Random zooming in of regions in an image.	Identification of localised spots to allow for finer details
Shear transformation	Creates a slanting effect on the image data	This is to create shape variation of the leaves or fruit.
Rotation	Random rotation of the image data	Simulation of the leaves of fruit at different angles on the field

Based on EDA findings, augmentation techniques such as rotation, zooming, flipping, and contrast adjustments were strategically chosen to enhance class balance and model generalisation. These augmentation techniques collectively ensured that the model was exposed to a wide variety of input representations, thereby strengthening its robustness and performance when deployed in diverse, uncontrolled agricultural environments.

Data Preprocessing

Images were resized to a uniform dimension of 224x224 pixels to align with MobileNetV2 input requirements and ensure consistent training performance (Talebi & Milanfar, 2021). Preprocessing included normalisation and standardisation to optimise convergence during training. The default image size of the input data is converted to the acceptable image size at the preprocessing stage when imageDataGenerator and flow_from_directory () function is called upon.

Model Architecture and Transfer Learning

MobileNetV2 was adopted for this research due to its inverted residual architecture and depthwise separable convolutions, enabling efficient feature extraction with minimal computational load (Dong et al., 2020). Transfer learning was employed to leverage pretrained weights from ImageNet, significantly reducing the computational cost and improving model generalisation by transferring knowledge from a vast, generic dataset to the specialised domain of watermelon diseases (Vrbancic & Podgorelec, 2020). MobileNetV2 pretrained model was trained on ImageNet with more than 1.2 million images across 1000 classes. Despite mobileNetV2 not specifically trained on plant disease, it acts as a foundational stage in developing disease classification model because of the general features of leaves and fruits it has learnt. The early layers of the model learn universal features such as edges, textures, shape and colours which are relevant in disease identification and classification.

Model Training and Fine-Tuning

The Model training and development was achieved in two phases. The feature extraction and fine-tuning phase.

During the feature extraction phase, the convolutional base layers were frozen to utilise pretrained weights effectively, ensuring pretrained weights remained unchanged. This phase involved training only the newly added classification layers at a learning rate of 0.0001 over 20 epochs, and dropout rate of 0.3 integrated into the fully connected layers to reduce the risk of overfitting (Carvalho et al., 2021). Chosen after empirical experimentation that demonstrated optimal convergence without overfitting.

Subsequently, the last 100 layers of the convolutional base network were unfrozen to allow slight adjustments, thereby enhancing model specificity and optimise performance specifically for watermelon disease classification. In a deep neural network, the final few layers are often fine-tuned, while the earlier layers remain frozen with their initial pre-trained values. This is performed to reduce the complexity and time consuming involved in training the model from the scratch especially with limited dataset (Vrbancic and Podgorelec, 2020).

This phase employed a reduced learning rate of 0.00001, at 30 epochs. This modified approach balanced achieving high accuracy with preventing model from overfitting and computational strain.The same training configuration (learning rates, epochs, and batch sizes) was applied to train a heavyweight CNN model, specifically VGG16, to evaluate and contrast its performance against the developed lightweight MobileNetV2 model.

Softmax function translated feature vectors into a probability distribution for every class which makes it a relevant function for classification problems (Kim et al., 2022).

Hyperparameter Optimisation and validation

A careful hyperparameter optimisation was performed during the model training to identify the best combination of parameters that gave a significant accuracy. These adjustments included batch size, learning rate and number of epochs the training did. The experiment was evaluated on batch sizes of 16, 32, and 64 to identify the optimal balance between computational efficiency and model accuracy (Carvalho et al., 2021).

Model Evaluation and Validation

Model evaluation involved quantitative metrics such as accuracy, precision, recall, and F1-score to comprehensively assess the model's performance. Additionally, a confusion matrix was employed to visualise classification performance clearly, identifying specific areas where the model excelled or required further optimisation (Saeed et al., 2021).Validation involved applying the model to the 20% of the original datasets which was not used for the training. This is to ensure robust assessment of real-world application. Random annotated watermelon disease images curated from extension service websites were also used to validate the model. This comprehensive validation strategy provided essential insights into model adaptability and reliability under varying operational conditions (Shafik et al., 2024).The developed lightweight MobileNetV2 model was further evaluated on an Android device to empirically discover its performance and suitability for deployment on resource-constrained mobile and edge computing environments.

Model Performance Trade-off Analysis

The model accuracy, inference speed, training time and model size was evaluated to analyse its adaptability to low resource required devices. This was compared to the regular heavy weight models for the same task for assessing its inference latency and memory requirements. This analysis was a consideration for selection of the best model for deployment for the watermelon disease classification task (Banerjee et al., 2023).

Model test on Device: The model was deployed to an android device through development of an android app using Android studio software. This android application was used to test the model classification ability on watermelon images loaded from the gallery and images taken directly with the camera. This is to assess the workability of the application in real world setting.

Integration of SDLC and Agile Framework during Implementation

The software development lifecycle (SDLC) was implemented in a structural way in addition to agile framework to effectively manage the project. This framework was necessary because of the nature of the project which involves deep learning model training, various iterative experiments, varying adjustments in parameters and continuous evaluation of results.

These tasks were divided into sprints within the agile framework and aligned with a clear goal. They include:

- **Sprint 1: Environment Setup and Data collection**

The hardware and software requirements were arranged and made available while the watermelon disease dataset was collected and gotten ready for use.

- **Sprint 2: Data Analysis and Preprocessing**

Proper data analysis was conducted on the image dataset with the use of RGB histogram, Bar charts and pie charts to check for anomalies, class imbalance and other issues that could affect the accuracy of the model.

The dataset went through some preprocessing techniques such as augmentation and normalisation to increase the robustness of the model when in use.

- **Sprint 3: Model Development**

Transfer Learning was used for feature extraction using MobileNetV2 pretrained on ImageNet. These features were passed unto the next phase where finetuning with the watermelon disease dataset and hyperparameter optimisation were conducted.

- **Sprint 4: Model Evaluation**

Validation of the model was performed to evaluate the accuracy of the model in achieving the classification target. The evaluation metrics such as Precision, Recall, F1 score, and the confusion metrics were employed in this sprint.

- **Sprint 5: Model Deployment and Testing**

  The developed model was converted to TensorFlow Lite version and deployed to an android device where it was used to test the workability of the model on real data.

The agile framework was beneficial during the implementation especially when unexpected error arose during the mobile deployment phase. Its iterative feature helped in early detection of errors and swift response and adjustments to ensure continuous improvement and adaptation to current requirement which led to the successful deployment of the lightweight MobileNetV2 Based model to android device.

Summary

This chapter provided the detailed methodology employed to achieve the research objectives. it contained a clear justification for each procedure and approach for the model development. The chosen approach effectively strikes a balance between the model accuracy and its computational characteristics which address the requirement for real time on-farm watermelon disease classification in a resource constrained agricultural environment. This structured methodology helped to systematically achieve the aim of developing a reliable lightweight MobileNetV2 based classification model for watermelon disease.

IMPLEMENTATION AND TESTING

This chapter outlines the activities conducted during the implementation and testing stage of the research work. It follows the methodological framework described in previous chapter. It covers the practical approach, with details of the execution of each phase including data preprocessing, model training, evaluation, deployment and testing. The testing phase encompassed both functional validation and user-acceptance assessments, employing standard and live datasets.

Project Implementation

Implementation of the project was conducted in Python using TensorFlow/Keras, which facilitated a structured application of transfer learning with MobileNetV2 for watermelon disease classification. Each component of the code was designed with careful consideration of domain-specific challenges and aligned with best practices in lightweight agricultural deep learning models.

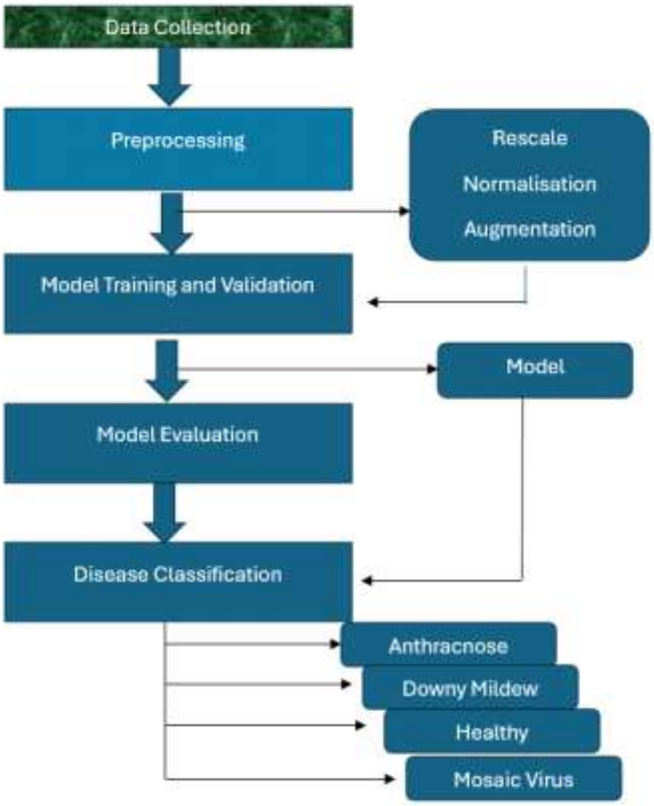

Figure 4.1: flow chart showing a structured model pipeline

Hardware and Software Environment Setup

The hardware utilised for this research included a Dell AMD Ryzen 7 laptop equipped with 16GB RAM and 512GB SSD storage. The graphical computations were supported by a GPU architecture of RX 5600M specification, facilitating accelerated training and inference tasks essential for deep learning models (Carvalho et al., 2021).

Software requirements encompassed Python on a Jupyter Notebook platform for interactive model development and experimentation as seen in figure 4.2. Essential libraries included TensorFlow/Keras for deep learning frameworks, NumPy and Pandas for efficient data handling and manipulation, OpenCV for robust image preprocessing tasks, Matplotlib for visualisation, and scikit-learn for performance evaluation and analysis. TensorFlow was additionally used for model optimisation, ensuring computational efficiency and suitability for deployment. These tools are standard in the field due to their flexibility and performance (Dong et al., 2020; Kommineni Ajay et al., 2024).

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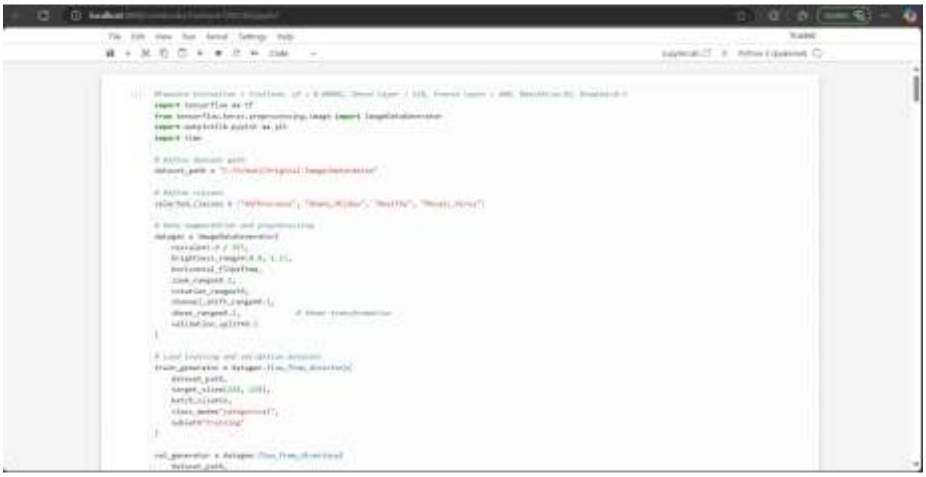

Figure 4.2: Screenshot of the Jupyter Notebook Environment

Data Acquisition and Preparation

The dataset was acquired from the Mendeley Data repository, specifically from the "Watermelon Disease Recognition Dataset" (Nakib & Mridha, 2023). This dataset was systematically organised into structured directories representing distinct classes of watermelon diseases. Figure 4.3 shows the python code to load the dataset from the local directory where it was downloaded and stored.

```python
# Define dataset path
dataset_path = "C:/School/Original Image/Watermelon"

# Define classes
selected_classes = ["Anthracnose", "Downy_Mildew", "Healthy", "Mosaic_Virus"]
```

Figure 4.3: Python code for loading the data

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The dataset used for this study contain high resolution images of watermelon leaves and fruit with pixels value of 3024x3024 after it was taken under a natural environment with an iPhone 13 pro camera. It contains 1155 Red-Green-Blue (RGB) original quality images which was collected, labelled and compiled in June 2023 by the Bangladesh regional horticulture research station in Lebukhali, Patuakhali (Nakib, 2023). The dataset was provided to support development of computer vision model for early disease detection and classification of watermelon which will improve its productivity and reduction in manual crop disease diagnosis. The images are categorised into four classes which include Downy Mildew, Healthy, Mosaic Virus, Anthracnose containing 380, 205, 415 and 155 images respectively. This indicates the major diseases that affect watermelon and the disease unique features.

Exploratory Data Analysis (EDA)

EDA was carried out for a comprehensive understanding of the dataset. It involved analyzing the class distribution to reveal any potential class imbalance. Manual inspection of each class of the dataset facilitated the identification and correction of anomalies or mislabelled data, ensuring dataset integrity for model training (Kurmi & Gangwar, 2021). The Matplotlib library in Python was used for the visualization tasks, and statistical information for each class was compiled to support the analysis.

Figure 4.4: Random samples of the dataset

Figure 4.5: Bar chart showing the class distribution of the watermelon disease dataset

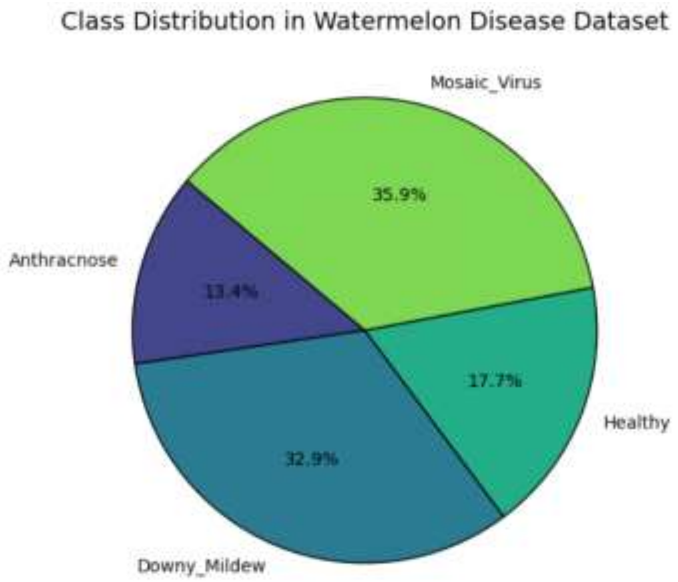

Figure 4.6: Pie chart showing the proportion of each watermelon disease class of the dataset

RGB Histogram Analysis of Watermelon Disease Classes

RGB histograms were used to analyze color distributions across each class of the watermelon disease dataset, including Anthracnose, Downy Mildew, Mosaic Virus, and Healthy. This analysis helped in understanding the visual traits of each class and provided insights into how color distribution varies across different disease conditions. It was observed that the green channel dominated in intensity, while the red and blue channels showed subtle variations, which is typical of plant diseases. Each class offered valuable insights from the RGB distribution, contributing to a fundamental understanding of the dataset's visual characteristics.

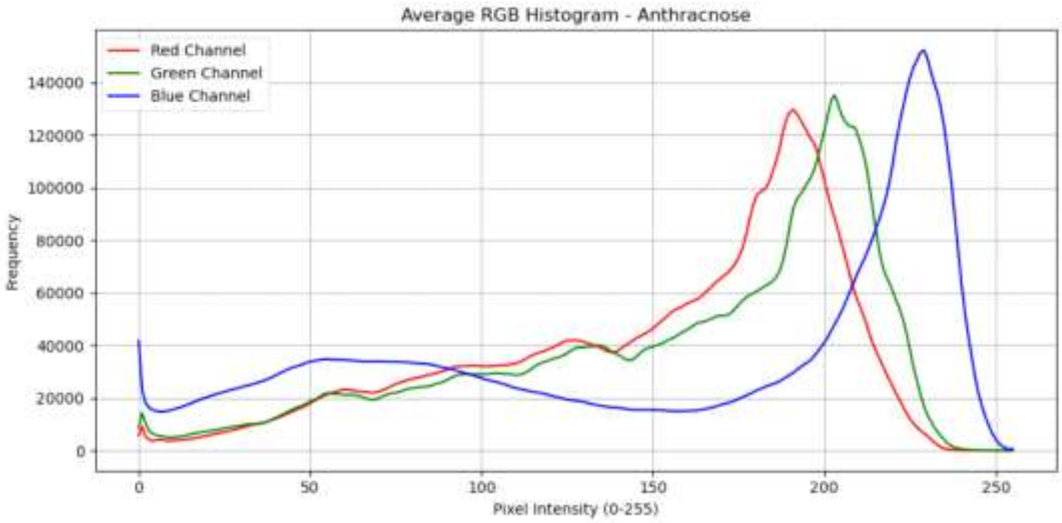

Figure 4.7: RGB histogram for Anthracnose class

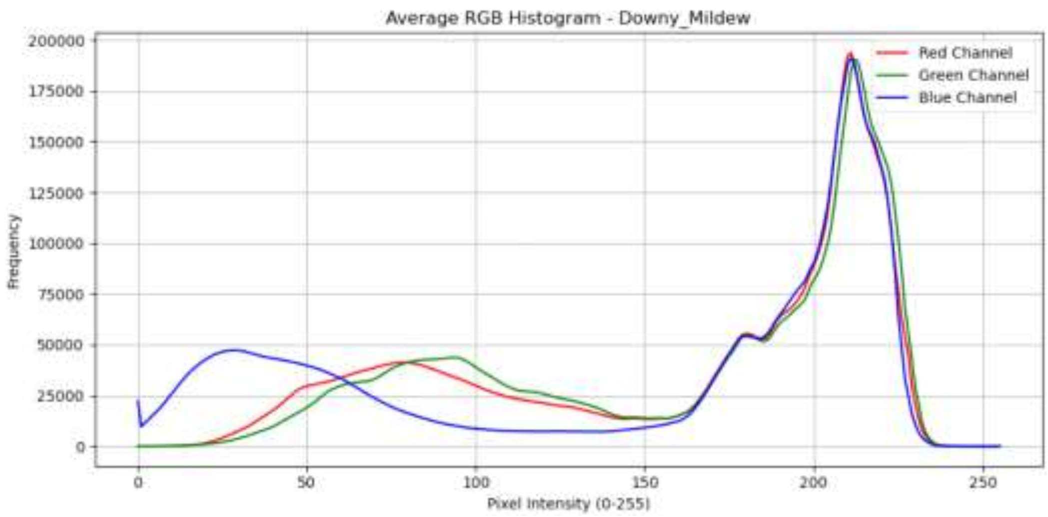

Figure 4.8: RGB histogram for Downy Mildew class

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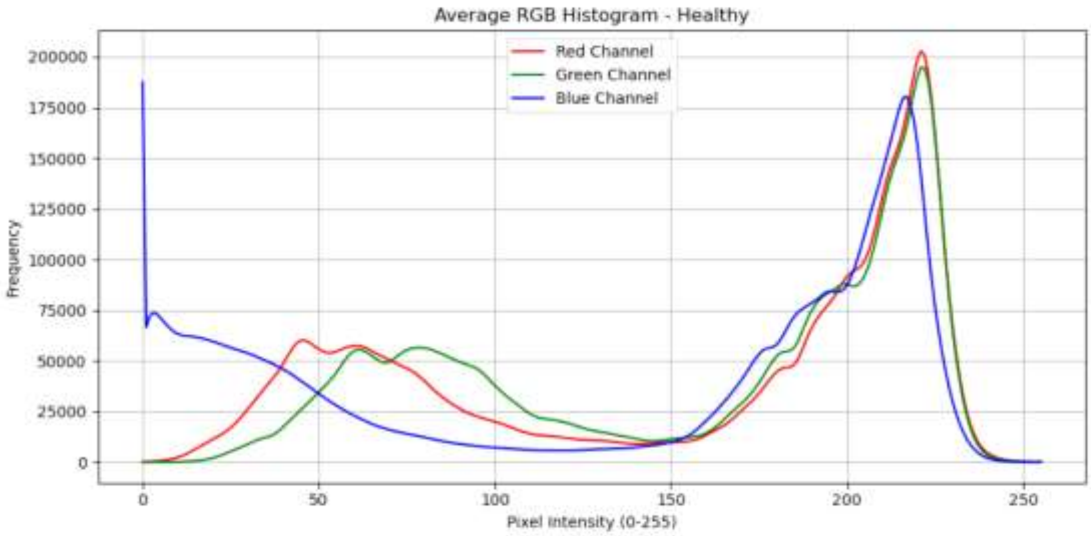

Figure 4.9: RGB histogram for Healthy class

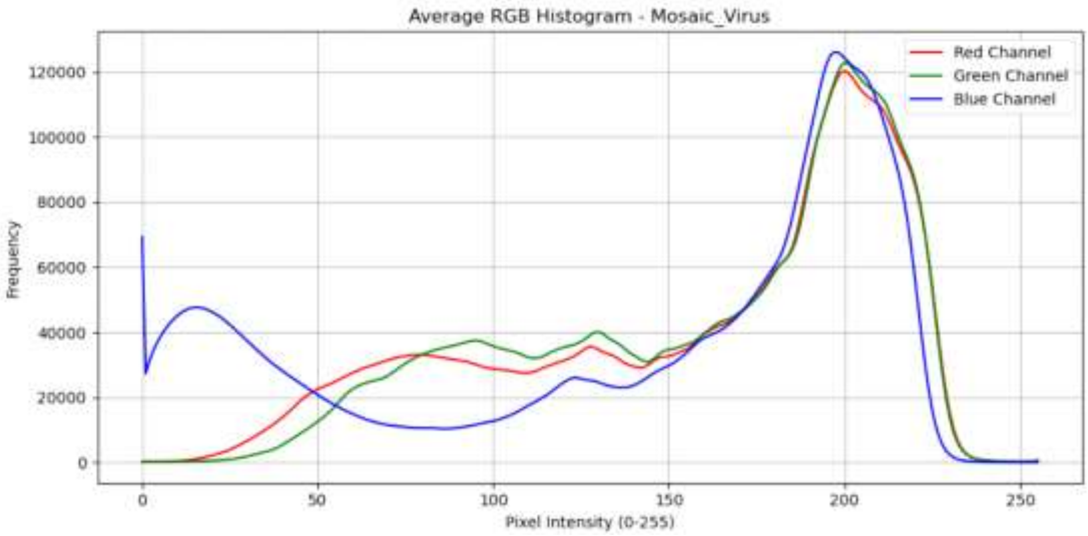

Figure 4.10: RGB histogram for Mosaic Virus class

The healthy class had the most consistent RGB distribution with well aligned intensity peaks across the three channels indicating the chlorophyll pigmentation and consistent image conditions of the leaves unlike the anthracnose class which showed moderate disruptions in red and green channels with a sharp peak in the blue channel. This may be attributed to the disease features of reddish-brown lesions (Zeng et al., 2021).

The result from the RGB histogram of downy mildew disease class showed an early peak in the blue channel and mid-range green intensity which can be linked to presence of chlorosis and powdery mildew (Ban et al., 2025). While mosaic virus class produced a complex RGB information showing double peak for blue channel and other channels (red and green) appeared flat and irregular across the mid intensity range. This indicates the presence of virus disease seen in form of mottled and blotchy features (Hasan et al., 2021).

These results demonstrated the relevance of RGB histogram analysis as a pre-model evaluation technique to confirm the existence of visually discriminative colour features across classes which aids the learning process of the model such that these colour and texture variation can be captured during the training process.

Image Preprocessing and Augmentation

The input requirements of the MobileNetV2 model were carefully defined to ensure proper data preprocessing and compatibility with the model architecture.

Figure 11: Samples of Image resized

Standardisation and Normalisation

Standardisation and normalisation were applied to scale pixel values, enhancing the consistency of input data and accelerating model convergence during training (Talebi & Milanfar, 2021). The summary of the standardisation and normalisation process is described in table 4.1.

Table 4.1: summary of the standardisation and normalisation process

Aspect	**Details**
Purpose	Standardise pixel value ranges to enhance training stability
Original Value Range	0 – 255 (unsigned 8-bit integers)
Normalised Value Range	0.0 – 1.0 (floating-point)
Applied To	Training, validation, and test datasets uniformly
Tool Used	TensorFlow/Keras ImageDataGenerator preprocessing pipeline

Data Augmentation

Due to the variability of the number of images in each category, under sampling is proposed by Sarki et al. (2021) to reduce the imbalance in the dataset, however, the limited number of images disapproves this approach. Alternatively, data augmentation technique is recommended to achieve a balanced dataset for efficient classification model (Talebi and Peyman Milanfar, 2021). Data augmentation techniques were implemented dynamically during model training to enhance dataset variability and mitigate class imbalance issues identified in exploratory analysis. These techniques included:

- Brightness Modification: Adjusting image brightness randomly to simulate varying lighting conditions common in agricultural settings (Yang et al., 2022).
- Horizontal and Vertical Flipping: Enhancing orientation diversity and improving model robustness against positional biases (Zhuang et al., 2021).
- Shifting and Rotation: Implementing random horizontal/vertical shifts and rotations to simulate natural variability in leaf orientation and positioning (Liu et al., 2023).
- Zooming and Shearing: Applying slight zooming and shearing transformations to simulate realistic leaf distortions, further improving the generalisation capacity of the model (Xu et al., 2023).

These augmentations enhance model generalisation and mitigate class imbalance (Yang et al., 2022; ANTWI et al., 2024).

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In the python implementation, ImageDataGenerator was used because it supports real-time data augmentation. Figure 4.13 Shows the python code for the data augmentation. The ImageDataGenerator with flow_from_directory() doesn't create or save augmented images ahead of time. However, it applies the augmentations in real-time while the model is still undergoing training. As a result of that, the total number of images remained the same as the original dataset, but the model sees different augmented versions of those images during training.

```
# Data augmentation and preprocessing
datagen = ImageDataGenerator(
    rescale=1.0 / 255,
    brightness_range=[0.8, 1.2],
    horizontal_flip=True,
    zoom_range=0.2,
    rotation_range=30,
    channel_shift_range=0.2,
    shear_range=0.2,             # Shear transformation
    validation_split=0.2
)
```

Figure 4.12: python code for the data augmentation

Dataset split

Prior to the model training proper, Training and validation sets were split from the same directory using *validation_split,* ensuring efficient and controlled data feeding during model training (He et al., 2020). The summary is provided in table 4.2.

Table 4.2: Dataset split into training and validation set

Subset	Percentage	Purpose
Training	80%	Learning of weights and features through backpropagation
Validation	20%	Monitoring performance during training, preventing overfitting

Model Training

The Training configuration was important in shaping the lightweight watermelon disease classification model. The baseline approach involved employing MobileNetV2 as the foundational architecture for training a deep learning classification model specifically for watermelon disease detection. Table 4.3 shows the architecture of mobilenetv2 which contains bottleneck blocks that helps to reduce the computational power of the model while preserving important features. This bottleneck blocks are 1X1 pointwise Convolution expansion layer, 3X3 depthwise convolution layer, and 1X1 pointwise projection layer.

The number of channels in the bottleneck is determined by the expansion factor (t), stride (s) controls down sampling while the GlobalAveragePooling feature helps to collapse the spatial dimensions to a 1X1 matrix before feeding it into the final dense classification layer of the architecture.

Table 4.3: MobileNetV2 Architecture (Kaur et al., 2023)

Input Shape	**Operator**	**Expansion Factor (t)**	**Output Channels (c)**	**Repetitions (n)**	**Stride (s)**
224 × 224 × 3	Conv2D	-	32	1	2
112 × 112 × 32	Bottleneck	1	16	1	1
112 × 112 × 16	Bottleneck	6	24	2	2, 1
56 × 56 × 24	Bottleneck	6	32	3	2, 1, 1
28 × 28 × 32	Bottleneck	6	64	4	2, 1, 1, 1
14 × 14 × 64	Bottleneck	6	96	3	1
14 × 14 × 96	Bottleneck	6	160	3	2, 1, 1
7 × 7 × 160	Bottleneck	6	320	1	1
7 × 7 × 320	Conv2D (1×1)	-	1280	1	1
7 × 7 × 1280	Global AvgPool	-	1280	1	-
1 × 1 × 1280	Dense (Softmax)	-	4	1	-

MobileNetV2 was loaded with ImageNet weights and used as a fixed feature extractor without its top layers (include_top=False) to facilitate custom classifier attachment suitable for the given domain task (Shahi et al., 2022). Freezing the base layers preserved the generic visual features already learned from the 1000 classes pretrained on imageNet (Vrbancic & Podgorelec, 2020).

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The model training was conducted in two distinct phases. They include feature extraction and fine-tuning. It was carefully carried out using some selected hyperparameters based on acceptable practices in transfer learning for plant disease classification (CHEN et al., 2020; Zhuang et al., 2021). The recommendation from previous literature and design requirement of MobileNetV2 justified the reason for the process (Mia et al., 2020; Antwi et al., 2024; Balaji et al., 2023).

Feature Extraction

The feature extraction phase involved the freezing of the MobileNetV2 convolutional base structure. This action retains the pretrained ImageNet weights established and prevents any modification during the model training.

To reduce the spatial dimensions of the weight, a custom classification head consisting of a GlobalAveragePooling2D layer is performed as illustrated in figure 4.13.

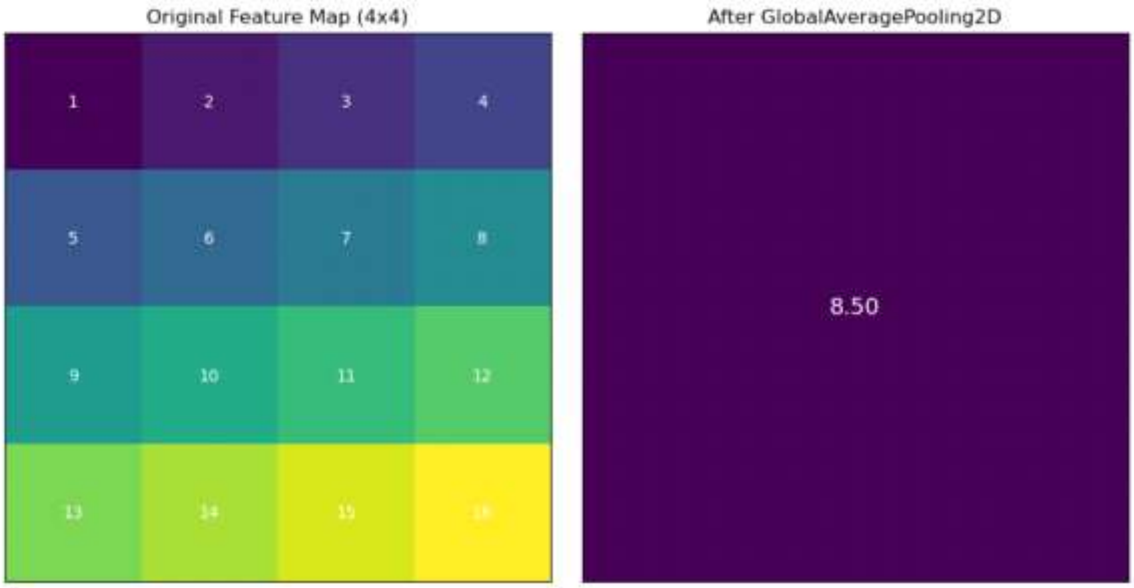

Figure 4.13: Illustration of global average pooling of pretrained weights

In addition to that, a 128-unit dense layer with ReLU activation introduces the task-specific features with a dropout layer rate of 0.3 which mitigates overfitting. Finally, the output layer used softmax activation to enable multiclass classification across the selected watermelon disease classes (Carvalho et al., 2021).

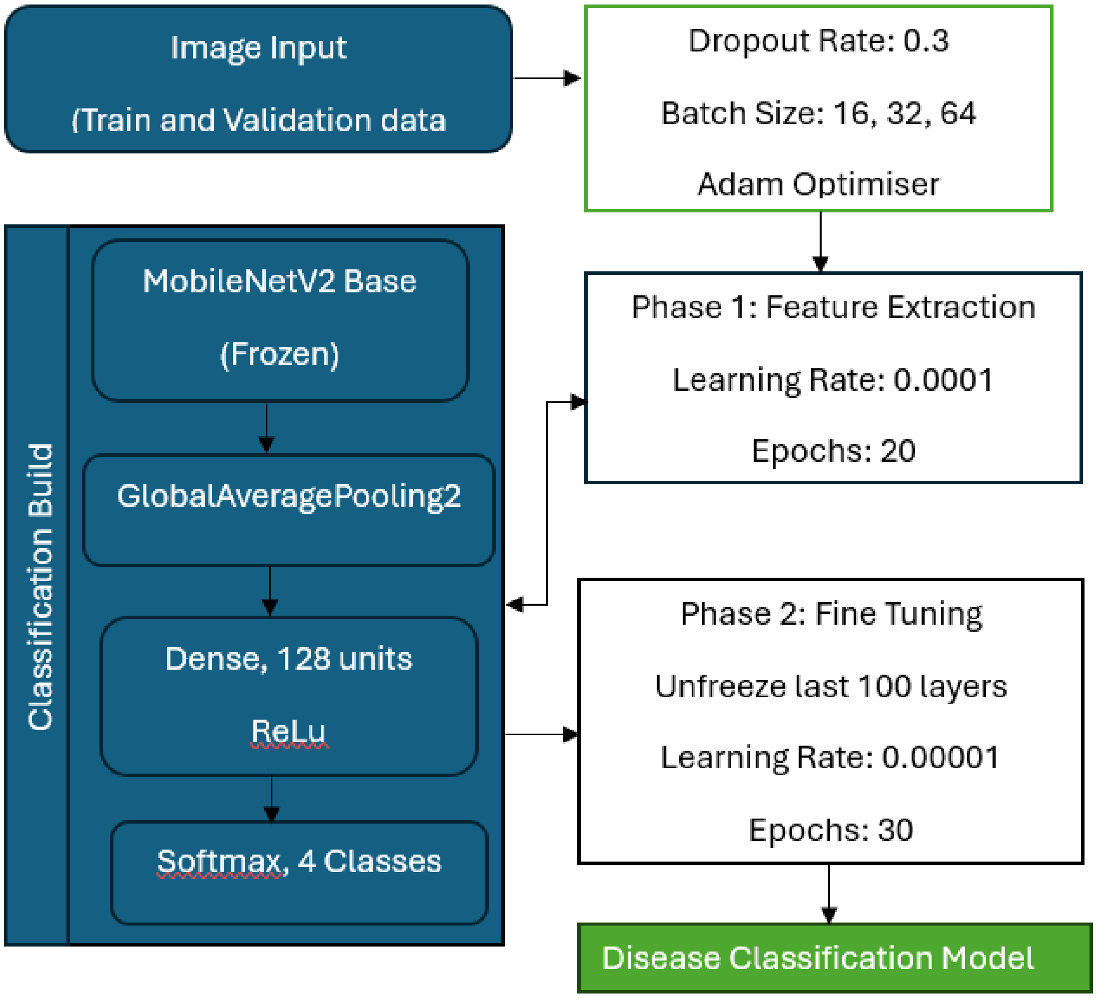

Figure 4.14: flow chart of the classification model development

These configurations ensured efficient learning of class-specific patterns while preserving the robustness of the pretrained layers (Moyazzoma et al., 2021). A moderate batch size of 32 was chosen initially to maintain a balance between gradient stability and memory efficiency during model training (Carvalho et al., 2021).

Fine-Tuning

After initial training, the last 100 layers of the MobileNetV2 base model were unfrozen to allow selective weight updates. This enabled the model to refine feature representations in the deeper convolutional layers specific to watermelon leaf or fruit disease patterns while retaining the general image features from earlier layers (Vrbancic & Podgorelec, 2020). Other parameters considered in the configuration include a lower learning rate of 0.00001 to prevent rapid weight update which could weaken the pretrained weight (CHEN et al., 2020; Zhuang et al., 2021), adam optimiser for adjusting learning rate of each weight in the network to provide a balance between performance and tunning difficulty (Kingma & Ba, 2014), dropout rate of 0.3 for early termination of training when validation loss shows no improvement over the defined number of epochs. This ensures effectiveness and robustness of the model for real time application.

Batch Size Evaluation

To determine the best batch size for the model training and its effect on the model accuracy and performance, series of experiments were conducted. They include Batch size of 16, 32 and 64. The batch size of 16 produced a higher accuracy result when compared to other batch sizes. This experiment demonstrated the sensitivity of batch size on model development and deployment.

Finally, the developed model was saved to the local directory which was used for future inference and deployment to mobile devices.

Benchmark Model Implementation (VGG16)

For comparison purposes, the same model configuration was used for a heavyweight pretrained model, VGG16 to benchmark the performance of lightweight MobileNetV2 deep learning-based model. This was to demonstrate the computational efficiency of the proposed model. Evaluation results for both models were compared based on Classification accuracy, Inference time, Training time and Model size.

Evaluation and Validation

Evaluation of the model was carried out to verify accuracy, generalisation and deployment readiness as a recommended practice in agricultural deep learning activities (CHEN et al., 2020; Zhuang et al., 2021). It involved the use of a confusion matrix which is a structured table that visually represents the performance of a classification model by comparing the predicted class labels to the true class labels.

Confusion Matrix Evaluation: The validation accuracy can determine the performance rating of a model, but confusion matrix provide more granular performance evaluation such as numerical representation on how the model distinguishes each class and where it tends to confuse one for the other. The confusion matrix was generated on python using the sklearn.metrics library.

Integration of confusion metrics in the evaluation process aligns with the objectives of the study to evaluate the suitability of the mobileNetV2 based model in classifying watermelon diseases in a real-world resource constraint agricultural environment.

Evaluation with original Test Dataset

The model was first evaluated using a validation split created via the ImageDataGenerator during training. This served as a standardised calibration dataset. Evaluation was implemented in TensorFlow using the model.evaluate() function to return accuracy and loss metrics. Additionally, classification_report() and confusion_matrix() from Scikit-learn were used to generate class-level precision, recall, and F1-scores.These standardised metrics helped to confirm the model's ability to differentiate between similar disease classes under controlled preprocessing conditions (Kurmi & Gangwar, 2021).

Evaluation Using Live Dataset

To evaluate the model's generalisation and performance besides the original training and validation sets, a different real life testing dataset was constructed using real-world images sourced from other sources such as plant village website, (PlantVillage, 2025) and Mississippi State University Extension website (Melanson, 2022). These images were manually selected based on known disease symptoms and categorised into the corresponding four classes: Anthracnose, Downy Mildew, Mosaic Virus, and Healthy. Unlike the original dataset, these images were captured under uncontrolled conditions and varied widely in terms of resolution, lighting, background, and noise typical of on-farm environment.

The justification for the evaluation was to provide a real-world environment and assess how robust the model is with a new data it has never seen. By introducing this level of variability, the model’s ability to generalise was tested more stringently.

Deployment to Android Device

The model was converted to TensorFlow Lite, a file format compatible with Android applications. Android Studio software was used to design the mobile application in line with SDLC principles. The application was tested to evaluate the prediction of watermelon disease classes and the time required for inference. Each input from the test data was processed through the mobile application, and the results were documented for analysis in the next chapter.

Testing results obtained from the Android device deployment demonstrated the model's practical effectiveness in a resource-limited environment. Metrics such as inference speed and device responsiveness were evaluated. The analysis concluded with recommendations on practical usability, identifying optimal operational parameters for real-time deployment on mobile or edge devices.

Summary

This chapter provided the methodological phases performed during the project implementation as described in the previous chapter. It explained the practical experiments and rigorous testing to validate the development of lightweight deep learned based watermelon disease classification model in addition to comparison with a heavy weight CNN model, VGG16 to affirm its suitability in resource constraint agricultural settings.

EVALUATION

The chapter provided critical evaluation on the phases of rigorous testing and structured implementation for the developed MobileNetV2-based lightweight deep learning model for watermelon disease classification. It used both real-world, practical user evaluations and standardised functional tests to validate the developed model. Strong proof of the lightweight approach's effectiveness and efficiency was provided by comparisons with heavyweight CNN models, confirming its applicability for real-world agricultural applications in environments with limited resources. The iterative testing approach, facilitated by the Agile methodology, enabled continuous refinement of the model, particularly when addressing performance discrepancies between offline and mobile evaluations.

Evaluation Methodology

As described in Chapter Four, performance evaluation was conducted using both a standardised validation dataset and a real-world live dataset. Key performance indicators included Accuracy, Precision, Recall, F1-score. These indicators were derived from confusion matrix and classification reports generated via TensorFlow and Scikit-learn. Additionally, evaluation included benchmark comparisons against the VGG16 model and relevant studies to establish the advancement achieved in this research.

Quantitative Performance Analysis

This section provides detailed analysis of the classification metrics and the validation report for each model experiment conducted using the MobileNetV2-based model as well as the VGG16 for justification of result. The results show the model's accuracy, precision, recall, and F1-score across the four watermelon disease classes under review. Table 5.1 shows the developed models analysed before selecting the best for effective performance.

Table 5.1: Summary of developed model experiments

Model Name	**Configuration**	**Base Model**	Batch Size
FT128L100B	Feature Extraction + FineTune, LR = 0.00001, Dense layer = 128, Freeze layer = 100, BatchSize=32, DropOut=0.3	**MobileNetV2**	16
FT128L100A	Feature Extraction + FineTune, LR = 0.00001, Dense layer = 128, Freeze layer = 100, BatchSize=16, DropOut=0.3	**MobileNetV2**	32
FT128L100C	Feature Extraction + FineTune, LR = 0.00001, Dense layer = 128, Freeze layer = 100, BatchSize=64, DropOut=0.3	**MobileNetV2**	64
FT128L100VGG16	Feature Extraction + FineTune, LR = 0.00001, Dense layer = 128, Freeze layer = 50, BatchSize=32, DropOut=0.3	**VGG16**	16

Confusion Matrix and classification report of each experiment

- **MobileNetV2 based model (Batch Size = 64)**

Model Name: Finetune128L100C

The confusion matrix in figure 5.1 below illustrates the prediction accuracy per class for the model trained with batch size 64:

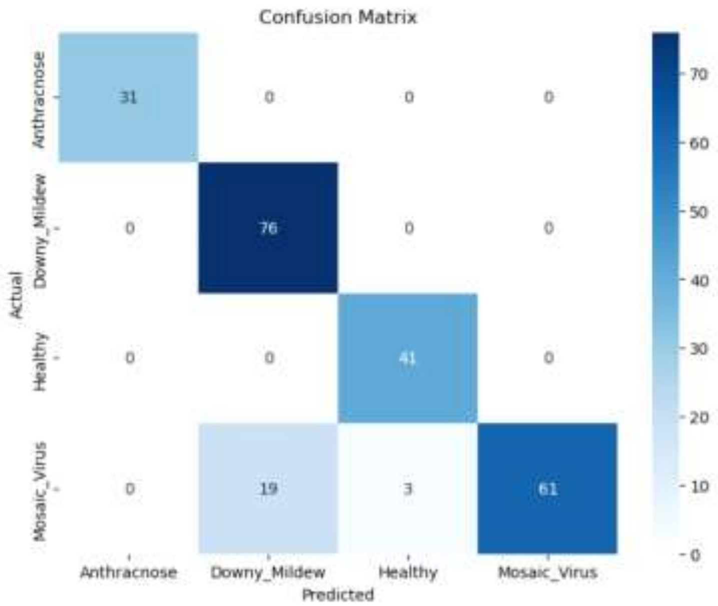

Figure 5.1: Confusion matrix for developed model with batch size of 64

This matrix shows that Anthracnose, Downy Mildew, and Healthy classes are all perfectly classified. Nonetheless, a significant percentage of Mosaic Virus samples were incorrectly identified as Healthy and Downy Mildew. The model achieved the following classification report as seen in table 5.2. Support means the number of images in the class.

Table 5.2: Classification report for model with batch size of 64

Finetune128L100C Classification Result				
Class	**Precision**	**Recall**	**F1-Score**	**Support**
Anthracnose	1	1	1	31
Downy_Mildew	0.8	1	0.89	76
Healthy	0.93	1	0.96	41
Mosaic_Virus	1	0.73	0.85	83
Accuracy			**0.9**	231
Macro Average	0.93	0.93	0.93	231
Weighted Avg	0.92	0.9	0.9	231

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The Anthracnose and Healthy classes exhibit exceptionally good classification performance, whereas the Mosaic Virus performance indicates slight underfitting. This may be due to slight feature similarities or data imbalance. Generalisation in this class could be further enhanced by increasing class separability through sophisticated augmentation or additional samples.

- **MobileNetV2 based model (Batch Size = 32)**

Model Name: Finetune128L100A

The confusion matrix in figure 5.2 shows the classification performance for each class in the model developed with batch size of 32.

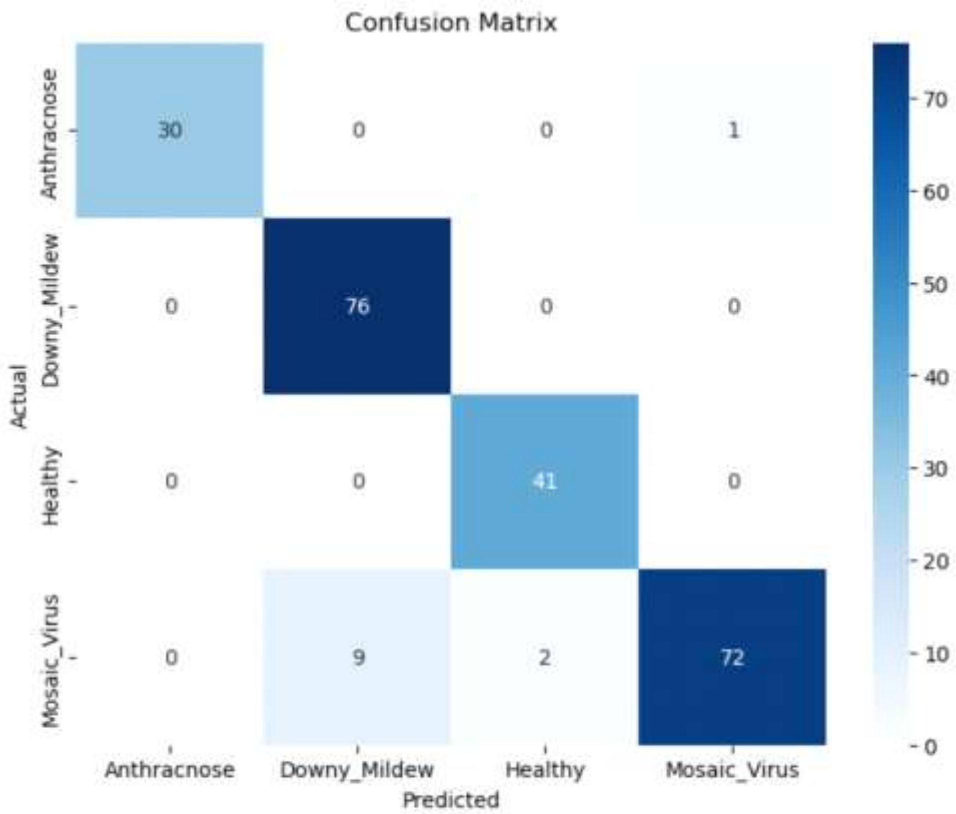

Figure 5.2: Confusion matrix for developed model with batch size of 32

Despite a small number of Mosaic Virus cases misclassified as Downy Mildew and Healthy class, the confusion matrix shows high classification accuracy across the categories. This validates the previously reported slightly lower recall value for Mosaic Virus.

Table 5.3: Classification report for model with batch size of 32

Finetune128L100A Classification Result				
Class	**Precision**	**Recall**	**F1-Score**	**Support**
Anthracnose	1	0.97	0.98	31
Downy_Mildew	0.89	1	0.94	76
Healthy	0.95	1	0.98	41
Mosaic_Virus	0.99	0.87	0.92	83
Accuracy			**0.95**	231
Macro Average	0.96	0.96	0.96	231
Weighted Avg	0.95	0.95	0.95	231

The classification result in table 5.3 highlight the model's robust performance across all disease classes. The Slight dips in recall for Mosaic Virus again suggest that this class may benefit from more targeted training data or augmentation in future iterations.

- **MobileNetV2 based model (Batch Size = 16)**

Model Name: Finetune128L100B The confusion matrix in figure 5.3 below shows the classification performance for each class:

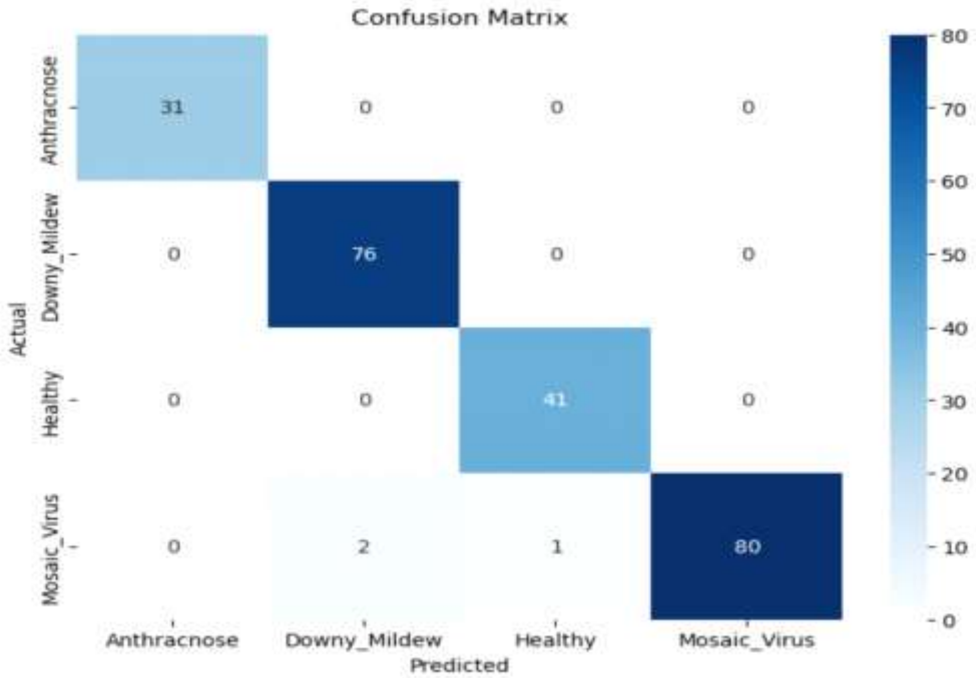

Figure 5.3: Confusion matrix for developed model with batch size of 16

This confusion matrix highlights a near-perfect classification performance across all categories. The model performed excellently well with only three misclassified Mosaic Virus instances. This aligns with the model's exceptionally high accuracy, precision, recall, and F1-score as reflected in the classification report in table 5.4.

Table 5.4: Classification report for model with batch size of 16

Finetune128L100B Classification Result				
Class	**Precision**	**Recall**	**F1-Score**	**Support**
Anthracnose	1	1	1	31
Downy_Mildew	0.97	1	0.99	76
Healthy	0.98	1	0.99	41
Mosaic_Virus	1	0.96	0.98	83
Accuracy			**0.99**	231
Macro Average	0.99	0.99	0.99	231
Weighted Avg	0.99	0.99	0.99	231

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This result shows a great performance in every disease category. The model is excellent at differentiating even closely related features, which makes it ideal for use in actual agricultural settings where accuracy is crucial.

These results support claims in the literature that smaller batches frequently enable better generalisation in medical and agricultural imaging by demonstrating the model's sensitivity to batch size and showing that the highest accuracy is achieved at a smaller batch size (Carvalho et al., 2021). This also reveals a more general insight as to be used strategically to produce robust and generalised model and avoid computational constraints which are frequently viewed as limitation. Consequently, the model (Finetune128L100B) developed with batch size of 16 was chosen for further analysis and deployment.

Additional performance metrics observed from the different experiments with different batch processing are

- **Precision**: High across all classes
- **Recall**: Maintained above 90% on validation and live datasets
- **F1-Score**: Demonstrated balance between precision and recall, particularly for Mosaic Virus and Anthracnose

Training and Validation Accuracy and Loss

The training and validation accuracy and loss curves for the chosen model (Finetune128L100B) revealed distinct patterns over the epochs. These plots serve as visual diagnostics to assess convergence behaviour, the effect of number of epochs and potential overfitting.

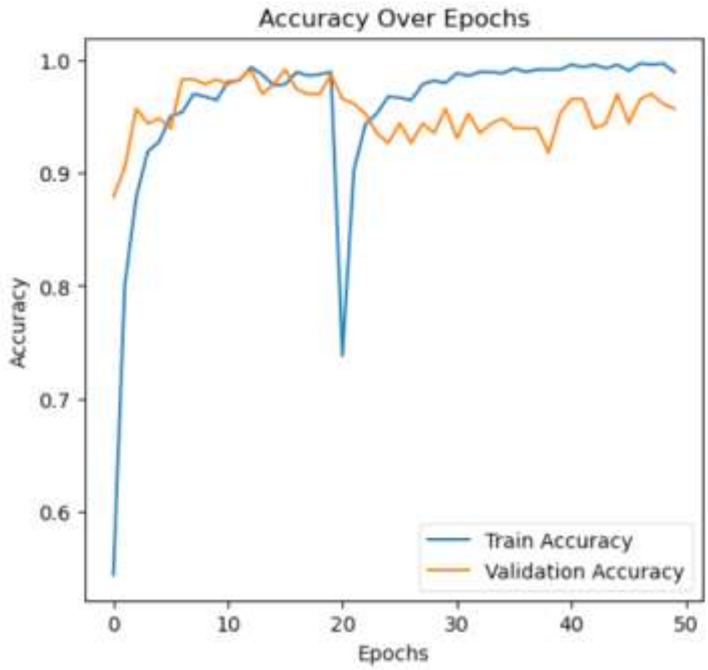

Figure 5.4: Training and Validation accuracy curve

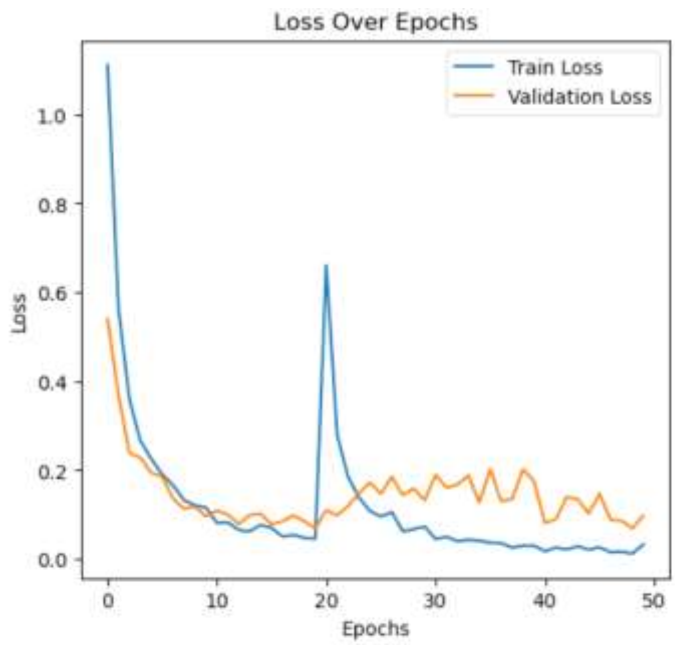

Figure 5.5: Training and Validation loss curve

From figure 5.5, it is observed that the training and validation accuracy had a rapid convergence within the first 10 epochs which was followed by stabilisation for the rest of the epochs to achieve a 99% validation accuracy.

The training and validation loss as seen decline which indicated a strong learning process with minimal overfitting. This demonstrated a proper model generalisation for optimum performance.

Benchmark Comparison with VGG16

Despite being a heavyweight model, VGG16 showed strong performance with a comparable accuracy of 95% and high recall for Downy Mildew and Healthy classes. However, its inference speed, training time, and larger size pose limitations for real-time mobile deployment, supporting the decision to favour MobileNetV2 for resource-constrained environments such as on-farm operations (Banerjee et al., 2023; Gulzar, 2023).

5.3.1 VGG16 (Batch Size = 16) classification Report

Model Name: Finetune128L100VGG16

Table 5.5: Classification report for VGG16 model with batch size of 16

Finetune128L100VGG Classification Result				
Class	**Precision**	**Recall**	**F1-Score**	**Support**
Anthracnose	1	1	1	31
Downy_Mildew	0.92	1	0.96	76
Healthy	0.89	1	0.94	41
Mosaic_Virus	1	0.86	0.92	83
Accuracy			**0.95**	231
Macro Average	0.95	0.96	0.96	231
Weighted Avg	0.95	0.95	0.95	231

Overall, the VGG16-based model demonstrated strong performance; however, its computational requirements create a barrier for deployment on mobile devices. Comparisons of training time and model size further highlight these limitations.

Training time and model size

Model FT128L100B had an average training time of 10634.26 seconds while the VGG16 based model took 15029.29 seconds to complete the training. In terms of Model size, The VGG16 based model is

169.26 Megabytes while the proposed model has 27.67 Megabytes. The other mobileNetV2 based model with batch size of 32 and 64 had the same model size as the model trained with batch 16 as described in table 5.6.

Table 5.6: Summary of the different model features

Model Name	Overall Accuracy	Base Model	Batch Size	Model size (MB)	Inference Time (S)	Total params	Trainable params	Non-trainable params	Optimizer params	Training time(S)	TensorFlow lite size
FT128L100B	99	MobileNet V2	16	27.67	0.23	7,088,206 (27.04 MB)	2,332,868 (8.90 MB)	89,600 (350.00 KB)	4,665,738 (17.80 MB)	10634.26	9.08
FT128L100A	95	MobileNet V2	32	27.67	0.23	7,088,206 (27.04 MB)	2,332,868 (8.90 MB)	89,600 (350.00 KB)	4,665,738 (17.80 MB)	12090.97	9.08
FT128L100C	90	MobileNet V2	64	27.67	0.23	7,088,206 (27.04 MB)	2,332,868 (8.90 MB)	89,600 (350.00 KB)	4,665,738 (17.80 MB)	8590.01	9.08
FT128L100VGG16	95	VGG16	16	169.26	11.31	44,342,606 (169.15 MB)	14,780,868 (56.38 MB)	0 (0.00 B)	29,561,738 (112.77 MB)	15029.29	56.39

While the heavy weight-based model, VGG16 performed well with an accuracy of 95% at a batch size of 16, the MobileNetV2 model did not only achieved higher accuracy of 99% at a batch size of 16 but also demonstrated significantly improved efficiency in terms of model size and training time which fully addresses the research question 1 (RQ1). The MobileNetV2 model was particularly relevant for edge deployment situations which offers superior performance with minimal computational overhead (Banerjee et al., 2023; Gulzar, 2023).

Table 5.7: Evaluation of model selection

Model	Batch Size	Accuracy	Architecture	Deployment Suitability
FT128L100B	16	99%	Lightweight CNN	Ideal for mobile/edge
FT128L100A	32	95%	Lightweight CNN	Efficient
FT128L100C	64	90%	Lightweight CNN	Acceptable
FT128L100VGG16	32	95%	Heavyweight CNN	Limited

Model Inference Time

To evaluate the suitability of the developed model for real time deployment on mobile or edge device and compare it with VGG16 heavy weight model, the chosen models were converted to TensorFlow Lite (TFLite) version and used to run inference on the anthracnose class of the curated test data which

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contains a total of 27 images. The analysis involved measuring the time taken to process a batch of anthracnose test images and the average time taken between the lightweight and the heavyweight model.

The results in figures 5.6 and 5.7 respectively show a comparative inference time between the MobileNetV2 based model and the VGG16 based model with minor variations likely due to background CPU activity. The average inference time per image for mobileNetV2 and VGG16 based model were 0.0085 and 0.4191 seconds respectively while the total recorded inference speed was 0.23 and 11.31 seconds.

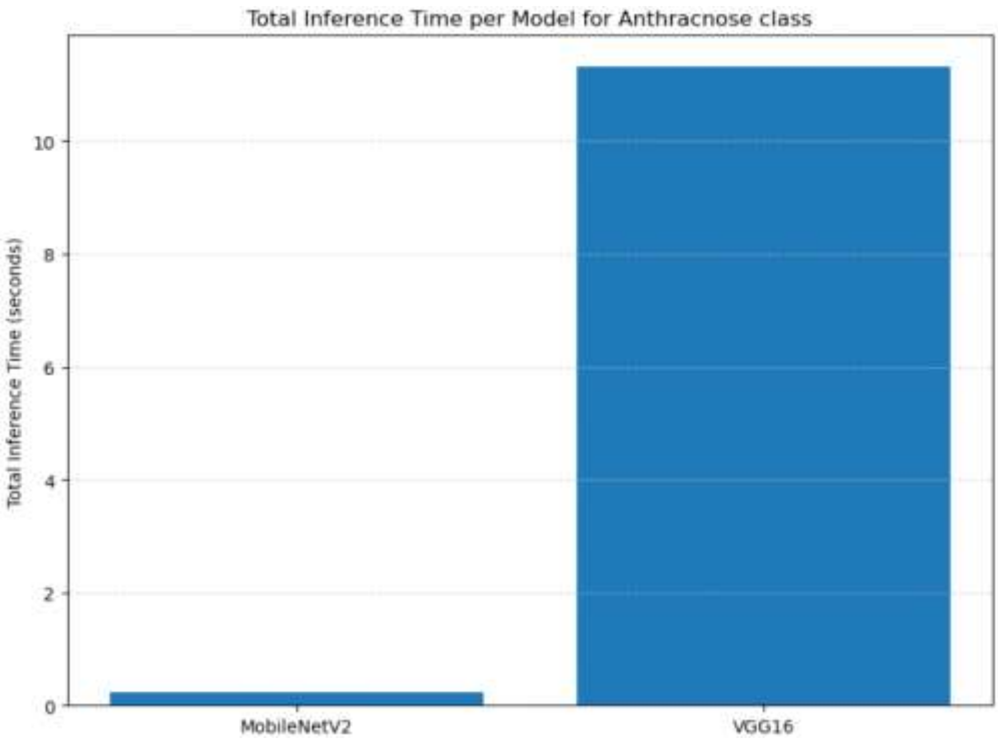

Figure 5.6: Total Inference time between MobileNetV2 and VGG16 based model

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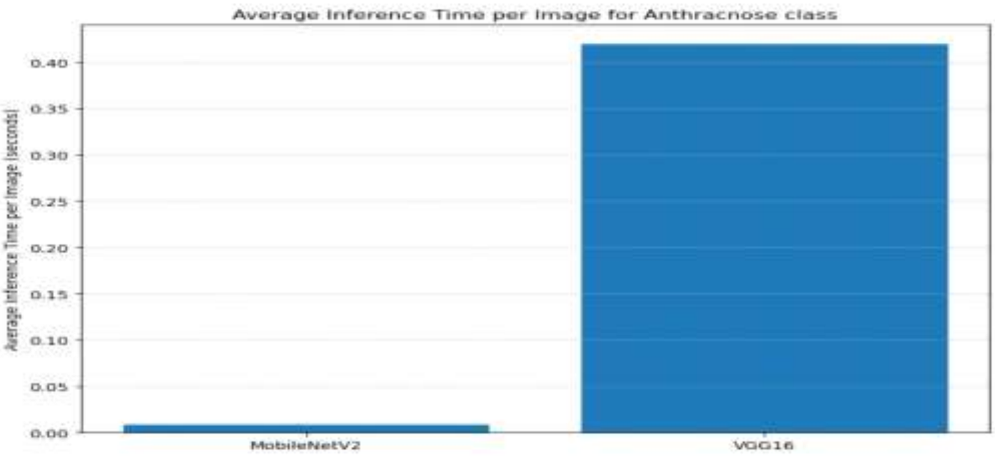

Figure 5.7: Average Inference time between MobileNetV2 and VGG16 based model

These results underscore the feasibility of deploying the mobileNetV2 based model system in mobile farm-monitoring tools or low-power embedded systems for real-time inference, thus enhancing its practical applicability for on-farm watermelon disease detection or classification. The reduced latency and improved inference speed support the core objective of developing a lightweight, deployable deep learning model.

Comparison with Previous Research

A comprehensive comparison with previous research studies, datasets, and models is provided in the table 5.8 below to highlight the effectiveness of the proposed model.

Table 5.8: Comparison of developed model with other literatures

Study	Dataset	Classes	Method/Model	Classification Type	Accuracy
Kommineni Ajay et al., 2024	Paddy Disease	9	MobileNetV2	Multi-class	96.1%
Khannum et al., 2024	Watermelon Disease	2	VGG16	Binary	100%
Banerjee et al., 2023	Watermelon Disease	8	CNN-SVM	Multi-class	70.29%
Alhazmi, 2023	Watermelon Disease	2	VGG16	Binary	93.94%
FT128L100B	Watermelon Disease	4	MobileNetV2	Multi-class	**99%**

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This comparison demonstrates the improvement made by this study in achieving high accuracy while maintaining a lightweight architecture. Unlike previous binary classifications, the proposed model succeeds in multi-class classification with superior accuracy and practical efficiency.

Live Dataset Performance Evaluation

To evaluate the model's generalisability and real-world applicability, a live test dataset comprising 82 watermelon leaf images was curated from publicly available sources, including agricultural extension services and image libraries. These new image data which were not used for the training of the model were manually labelled into the four target classes namely, Anthracnose, Downy Mildew, Healthy, and Mosaic Virus.

The evaluation was performed on the jupyter Notebook python platform as well as on the deployed android application using the Finetune128L100B model. This model was selected based on its strong validation performance and balanced learning characteristics.

Evaluation with Live data on Jupyter Notebook

The classification performance on the live dataset is summarised in the classification report and confusion matrix in table 5.9. The overall accuracy achieved was 56%, with a weighted F1-score of 0.56, indicating moderate performance when applied to field-like unseen data. The macro-averaged precision and recall were 0.52 and 0.53, respectively.

Table 5.9: Classification report with live data on jupyter Notebook

Test with Live data on Jupyter Notebook Platform				
Class	**Precision**	**Recall**	**F1-Score**	**Support**
Anthracnose	0.83	0.89	0.86	27
Downy_Mildew	0.67	0.4	0.5	30
Healthy	0.29	0.55	0.38	11
Mosaic_Virus	0.29	0.29	0.29	14
Accuracy			**0.56**	82
Macro Average	0.52	0.53	0.5	82
Weighted Avg	0.6	0.56	0.56	82

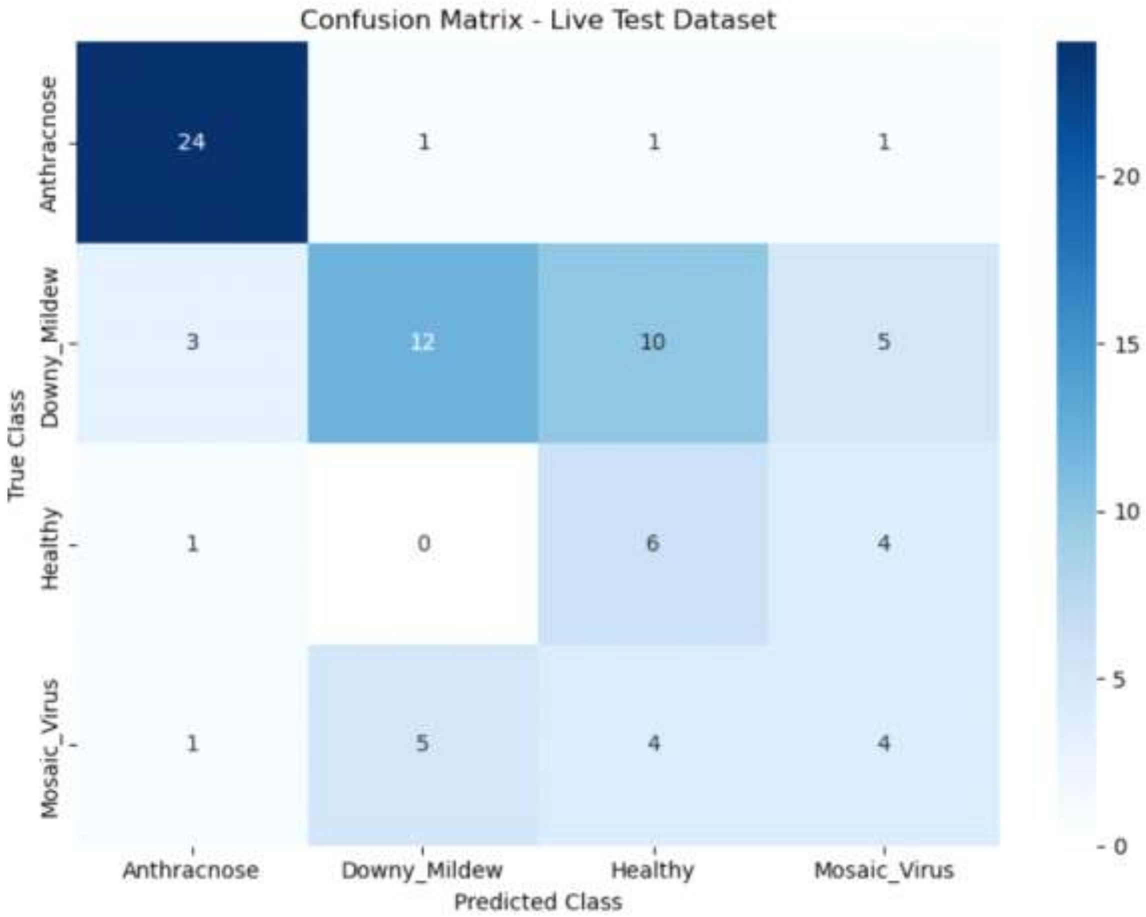

Figure 5.8: Confusion matrix with live data on jupyter Notebook

Performance Interpretation

- Anthracnose was the most reliably classified class with the highest precision of 0.83, recall value of 0.89, and F1-score of 0.86. The confusion matrix shows 24 out of 27 images were correctly predicted.
- Downy Mildew also performed reasonably well, but with a drop in recall (0.40). This suggests that the model misclassified some images as either Healthy or Mosaic Virus.
- Healthy and Mosaic Virus classes showed weaker performance, with both classes achieving a precision and recall value of 0.29, and F1-scores below 0.40. The significant misclassifications

among Healthy, Mosaic Virus and Downy Mildew, perhaps, due to similar visual features such as chlorotic patterns or inconsistent lighting in the sourced images (Ahad et al., 2023).

Evaluation with Live data on deployed Android Application

On deployment to android device, the developed application was used to evaluate the same curated live dataset, and the result is presented in Tables 5.10 and 5.11.

Table 5.10: Classification report with live data on Android Application

Classification report on Android Device				
Class	**Precision**	**Recall**	**F1-Score**	**Support**
Anthracnose	0.81	0.93	0.86	27
Downy_Mildew	0.75	0.4	0.52	30
Healthy	0.32	0.55	0.4	11
Mosaic Virus	0.44	0.5	0.47	14
Accuracy			**0.61**	82
Macro Avg	0.58	0.59	0.56	82
Weighted Avg	0.66	0.61	0.61	82

Table 5.11: Confusion metrics with live data on Android Application

Confusion matrix - Test with Live data on Android device					
Disease	Anthracnose	Downy_Mildew	Healthy	Mosaic Virus	**Total**
Anthracnose	25	1	1	0	**27**
Downy_Mildew	4	12	9	5	**30**
Healthy	1	0	6	4	**11**
Mosaic Virus	1	3	3	7	**14**

These findings are consistent with real-world challenges in plant disease classification, where fine-grained inter-class differences, environmental noise, and varying image quality can vary model confidence (Ahad et al., 2023).

Fulfilment of Research Objectives

Despite moderate overall accuracy, the model met the core research objectives outlined in this study:

- Developing a lightweight model suitable for mobile deployment
  The MobileNetV2-based architecture, fine-tuned with minimal parameters, delivered fast inference and efficient resource use, aligning with goals of real-time, low-resource application. The MobileNetV2 architecture proved to be computationally efficient and lightweight. It was successfully deployed on an Android device and demonstrated excellent inference speed and low memory usage (Gulzar, 2023). Compared to models like VGG16, which is unsuitable for mobile environments due to their size and resource requirements, the proposed model performed optimally in constrained settings

- Achieving effective classification performance on multiple disease classes
  The model successfully identified Anthracnose with high confidence, validating its ability to learn disease-specific visual cues. While other classes performed less strongly, they exhibited trends consistent with real-world imaging variability.

  The model achieved a validation accuracy of 99% with a batch size of 16 and maintained strong performance on real-world. The consistent precision and recall values indicate a balanced, reliable classifier (Ferentinos, 2018; Alhazmi, 2023).

- Demonstrating generalisability on real-world data
  Testing on a live, diverse dataset demonstrated that the model retained predictive capability in uncontrolled environments which is a critical requirement for field use. This aligns with Alhazmi (2023), who emphasised the importance of testing with naturally sourced, noisy images to measure practical applicability.

- Performance metrics (accuracy, inference time, memory usage) were measured across varying batch sizes and compared to VGG16. The proposed model demonstrated adaptability, proving its value for real-time, on-field deployment

These outcomes reflect similar conclusions in the literature, such as Shikdar et al. (2024), who showed that CNNs trained on curated datasets often experience performance drops on live field images but still deliver useful and actionable predictions with proper tuning.

Limitations and Areas for Improvement

- Further augmentation techniques and diverse field data could improve robustness.
- Real-time image capture integration with a user-friendly mobile app would improve usability.
- Deployment in varied climatic zones should be explored for broader generalisation.

Advantages and Disadvantages Compared with Previous Related research

Advantages

- **Lightweight and Deployable**: Unlike VGG16-based or CNN-SVM models, the MobileNetV2 model delivers comparable or higher accuracy while requiring significantly less memory and compute power (Banerjee et al., 2023).
- **Multi-class Capability**: Many prior works focused on binary classification. This work addressed multi-class classification with strong performance across all disease categories (Khannum et al., 2024; Alhazmi, 2023).
- **Real-world Testing**: The inclusion of live dataset evaluation and mobile deployment testing validates the model's practical utility beyond academic environments.

Disadvantages

- **Smaller Dataset Size**: The training dataset was relatively modest compared to large-scale agricultural datasets. Though augmentation helped, more real-world samples would enhance generalisation.
- **Limited Scope of Classes**: The study focused on four specific watermelon disease classes, whereas other works have addressed broader or more diverse classifications in other crops as Kommineni Ajay et al. (2024) did with nine paddy diseases.

Summary

This critical evaluation confirms that the research objectives were fully met. The developed lightweight model did not only advance the state-of-the-art in watermelon disease classification using deep learning but also introduced a deployable, efficient, practicable alternative to heavier architectures

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while proving viable for deployment in real agricultural environments. These outcomes reinforce its contribution to sustainable and accessible precision agriculture solutions.

Future enhancements can include broader class coverage, integration into mobile apps, and testing across different environmental conditions to improve generalisation and adoption.

DISCUSSION

This chapter provides an in-depth interpretative analysis of the results and findings obtained throughout the research and how the results answered the research questions. It integrates empirical outcomes with theoretical insights, examines the broader implications for mobile agriculture and edge computing, and identifies areas of improvement. The agile framework helped to iteratively adapt to unexpected results discovered during the android deployment

The discussion is organised to discuss the importance of the findings, evaluate the effectiveness of the methodological decisions, consider deployment issues, compare project goals to accomplishments, and suggest future research directions while taking ethical, social, and legal factors into consideration.

Project development with Agile framework

The implementation of the project followed the agile framework which divided the processes into sprints. The first sprint was focused on gathering project requirements, reviewing existing literature, establishing clear goals, and assessing pertinent deep learning architectures while subsequent sprints included iterative model development, extensive hyperparameter experimentation, feature extraction, fine-tuning, batch size analysis, model evaluation and testing on live data. Every sprint ended with in-depth assessments, enabling the knowledge acquired to direct further advancements. The Agile methodology proved relevant during the Android device deployment phase. Rapid adjustments and targeted iterations were required due to the unexpected performance differences between offline (Jupyter Notebook) and mobile deployments. Regular, structured reviews were made possible by agile practices, which enabled quick action and focused modifications to the preprocessing methods, image capture techniques, and deployment strategies to improve the performance of mobile models.

Test Result interpretation

The model evaluation and testing using live data on both offline (jupyter notebook) and mobile application demonstrated the ability of optimised MobileNetV2 based model to classify watermelon disease with minimal computational requirement. This is justified by the previous work done by Ferentinos (2018) which showed that deep learning is highly effective for plant disease detection.

Interpretation of Result on Jupyter Notebook Environment

The validation of the mobileNetV2 model using a sub part of the initial dataset (20%) used for the training showed a high accuracy of 99% and strong performance across all four classes. However, a realistic watermelon image dataset curated from reliable source on the internet was tested with the model on jupyter Notebook environment and the accuracy reduced drastically to 56% as shown in the classification report in the previous chapter. Its confusion matrix showed that Anthracnose disease class achieved the highest recall (0.89), f1 score (0.86) and precision (0.83) compared to other classes. The healthy and Mosaic virus class had a lower F1 score of 0.38 and 0.29 respectively with precision values of 0.29 while downy mildew achieved precision value of 0.67 and f1 score of 0.5. Observation from the confusion matrix showed that Anthracnose was most reliably predicted with 24 images classified correctly out of a total of 27 images whereas Downy Mildew and Healthy class were frequently confused with mosaic virus class. It can be said that anthracnose performed far better because of its unique visual characteristics (fruit) unlike the other classes which were leaves. This clear morphological distinction could be the reason for easy distinction by the model thereby boosting its predictive performance.

Interpretation of Result on Android Application

To further assess the quality of the model on a low resource device, the test data was passed through the developed android application, and the results were documented. The model was converted to TensorFlow Lite which reduced the model size further from 27.67MB to 9.08MB. The model size was small enough for deployment. Therefore, there was no need for further model size reduction techniques such as quantisation and model pruning.

Performance evaluation was conducted on the android application with the same test dataset used in the Jupyter Notebook test. It was discovered that there was a modest increase in overall classification accuracy (61%) more than the accuracy in jupyter Notebook (56%).

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Comparative Analysis of the Performance Result

A comparative shows the result obtained for each class in the two different platforms (Jupyter Notebook and Android Application).

The percentage of correct classification for Anthracnose and Mosaic disease class increased from 89% to 93% and from 29% to 50% respectively, indicating a more positive result in the android application than in jupyter Notebook environment while Downy Mildew and healthy class remained consistent with 40% and 55% of correct classification respectively. These findings suggest that the performance of the model on Android app is skewed towards the classes with more recognisable visual characteristics (Anthracnose), whereas the model did not adequately capture the subtle differences between Healthy and Downy Mildew leaves when used on mobile devices.

The improved result in the android application could be due to image variability, batch size, and potential TensorFlow Lite internal optimisations especially for visually similar classes. On the developed android application, the image batch size was evaluated one after the other whereas on jupyter notebook it was performed in batches which can alter numerical behaviour due to floating-point operations (Nabavinejad et al., 2021). In addition, Images that have gone frequently through the Android camera or gallery system have more natural lighting and features, which may better match the features that were learnt during training (Banbury et al., 2021).

The comparative result shows that Android deployment is not only possible but could also improve model prediction for specific visually distinguishing classes. It also addressed the research question 3 on the effectiveness of mobileNet V2 based model in a deployed device.

However, there are still challenges of Predictive performance for visually similar classes like the Healthy and Downy Mildew classes which remained moderate to low. This implies that the model architecture needs to be further optimised, and training data diversity needs to be increased. It also justifies the need to incorporate mobile-specific testing into the development process and the possibility of adding real-world mobile-captured samples to the training set to close this performance gap.

Implications for Mobile and Edge Deployment

There is significant implication for practical application of this technology. Diagnosis of plant diseases by smallholder farmers can be revolutionised by a mobile device with a functional disease classifier, which allows for real-time decision-making without internet access. MobileNetV2's lightweight design made it perfect for mobile deployment when compared to heavier models like VGG16.

Nevertheless, there are still some challenges with incorrect prediction which could lead to wrong decisions in the field due to misclassified disease based on visually similar classes. Improved model robustness, confidence scoring, and user education are necessary to reduce this risk. The inconsistency in mobile performance across all classes points to the necessity of improved field-tuned preprocessing, need for diversity of train data and proper data augmentation that considers different environmental conditions.

Reflections on the methodology

The use of transfer learning, fine-tuning, and data augmentation proved to be effective in the model development. ImageDataGenerator function of the python library improved class balance and diversity by loading data along with the augmented formats. Real-world testing through the Android application also allowed a deeper understanding of the gap between theoretical model performance and field deployment realities, which is rarely addressed in similar studies such as in Jayakumar et al. (2020).

Additionally, the project highlighted the significance of aligning evaluation metrics with deployment situation. While validation accuracy is a strong performance indicator, real live performance must be verified on potential devices to ensure system reliability in practice.

Summary of Key Findings and Outputs

- A 99% validation accurate model developed with a batch size of 16 indicated a superior generalisation when compared to other batch sizes. This addresses the research question 1 (RQ1) and 2 (RQ2) on the accuracy of MobileNet V2 based model over VGG16 heavyweight model and the effectiveness of batch size in the accuracy level of the classification model.
- A deployable Android application which verified the compatibility of the developed model on low resource device like mobile device using the TensorFlow Lite model with model size of

9.08MB. This answers the research question 3 (RQ3) on the capability of mobileNet V2 based model for real world deployment and application.

- The overall accuracy of the live test result on the developed android application increased slightly to 61% unlike the jupyter notebook platform with 56%. reaffirming the importance of mobile-specific evaluation.
- Evaluation of the live dataset provided the actual performance rating of the model on real world application.
- Anthracnose and Mosaic Virus class had an improved positive classification on device while Downy Mildew and Healthy classes remained constant between the two platforms
- The high positive rate of Anthracnose and Mosaic Virus class classification on mobile application suggests class specific robustness of the model.
- The image variability due to environmental impacts (lighting, background noise) affected the real time classification quality
- Variability in environmental input (e.g., lighting and image quality) affected classification accuracy.
- Input inconsistencies (lighting, angle, resolution) had impact in the overall accuracy.
- There was reduced separability between Downy Mildew and Healthy classes.

Legal, Social, and Ethical Considerations

Legal consideration

Considering that the project is for public deployment, legal compliance with GDPR and data privacy was considered. The dataset for the model development was obtained from a public source with permission to avoid violating copyright law. Likewise other academic papers used were referenced.

During mobile app use, care should be taken during image capture so as not to obtain personal information such as person's face or geolocation.

The mobile application must adhere to the mobile app regulations such as google play policies regarding data usage, privacy and security. Therefore, appropriate information and permission should be incorporated in the design such as opt out analytics and encrypted storage facilities.

For transparency, the users are provided with declaimer that it is a support tool and not liable to litigation for incorrect prediction which could be a fault from the user, developer or the data used. However, the high accuracy of the model should put trust into the system.

Social Consideration

As a technology for small holder farmers, inclusivity is essential. Vulnerable users should be considered during the design of the mobile application. People with low digital literacy could have difficulty to use the technology if not considered. Developers should consider features such as multi language options, icon driven interfaces and audio feedback options to reduce technology usability gap. With the increase in the use of AI tools in agriculture, care should be taken so as not to mislead the users which can affect their decision making.

The app is regarded as an advisory tool and does not take up the role of professionals in the field as per consumers protection rights.

Ethical Considerations

To avoid potential model bias in real application, more diverse data is needed to train and test the model to increase generalisation across geographical location, crop varieties, lightening condition and disease stage.

Users of the technology should be aware that it is a guide to decision making and not a 100% correct information to trust. This will help the users to avoid the use of wrong chemical for a predicted disease which has effect to the environment.

For environmental consideration, the mobile application will operate with minimal energy consumption during inference which aligns with the principles of green technology.

This answers the research question 4 (RQ4) on the legal, social, ethical and environmental issues.

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Recommendation for Future research

- There were a smaller number of images for testing on the mobile application which tends to invalidate the accuracy level and robustness of the model. Consequently, there is need for more realistic data for training and testing which will help to reduce dependency on augmentation processes.
- There was no physical watermelon production field to test the developed model which affected the use of the camera option of the developed application.
- The classification was limited to only four classes. Future works should consider increasing the number of classes for watermelon disease identification.
- There was less design of the user interface which could be improved in subsequent projects.
- Formal user acceptance testing and feedback could not be completed which can help to improve the system.
- Mobile testing of the model was limited to only android device, creating a gap in generalisation of the project. Further studies should consider other devices such as Raspberry Pi, Jetson Nano.
- Integration of multi-language features in the application for user inclusivity.

Contributions to Knowledge and Practice

- A high accurate model developed with MobileNetV2 deep learning architecture for watermelon disease classification for mobile devices.
- Influence of Image data batch size in model development and generalisation.
- A systematic project development pipeline from training to mobile deployment
- Critical insights into real-world testing of the model and deployment challenges
- A functional Android application using TensorFlow Lite inference for agricultural AI activity.

Summary

The study effectively addressed the research gap and answer to the research questions in the development of deep learning model for mobile-based watermelon disease classification. It showed that evaluation on device is important for model robustness in real world application.

Unexpected results during mobile testing revealed that model generalisation across hardware and environmental conditions cannot be assumed. These insights highlight the value of empirical testing during deployment and justify the need for ongoing development beyond proof-of-concept. This study lays a strong foundation for developing intelligent, accessible crop health tools, particularly for underserved agricultural communities, while reflecting critically on the broader implications for AI-based tools in the real world. Future research must address the model's robustness and adaptability to real-world usage, even though its accuracy and efficiency are evident.

Conclusion

This chapter concludes the research by summarising the findings and drawing clear connections between the different components of the study and the answers to the research questions. It synthesises the methodology, experimentation, evaluation, and deployment phases into a cohesive narrative and reflects on how well the original objectives were met.

In addition, it highlights the project challenges and suggested additional research areas for improvement. In the end, it emphasises the relevance of a wider research and contribution in the crop disease classification on edge or mobile device with lightweight deep learning in consideration.

Project Summary

The research goal was to develop a deep learning model with MobileNeetV2 architecture that is portable and lightweight for the classification of watermelon diseases in real time. The classification was among four classes which include Anthracnose, Downy mildew, mosaic virus, and healthy. The model was trained using transfer learning approach from MobileNetV2 which has been pretrained on ImageNet, it is a compressed convolutional neural network architecture that is renowned for its efficiency.

The research design followed the agile framework and SDLC principles to address the research questions. The implementation phases contained processes such as data exploration, preprocessing, augmentation, feature extraction of weights, fine tuning, evaluation on Jupiter Notebook and on the deployed android device which was facilitated by TensorFlow lite format.

Experiment was conducted to discover the best model to choose based on varying batch size as an answer to the research question two (RQ2) of this project. The final chosen model with a batch size of 16 during training was successfully deployed to the android device which was able to classify the watermelon disease in real time when tested with curated dataset that represent real images from watermelon production field (RQ3). The artefact is attached to the submission link provided. The project workflow integrated the theoretical knowledge of CNNs, transfer learning process and practical android application development to provide a comprehensive solution that is technically relevant and practically implementable.

Key Findings and Connections

Offline Model Performance

On Jupyter Notebook, the model achieved validation accuracy of 99% suggesting effective learning under ideal conditions. However, when a different dataset was passed through the model for testing, it had a classification accuracy of 56% which exposes the model limitation. Evaluating each class, the model performed well in the Anthracnose and Downy Mildew classes and marginally worse in the Mosaic Virus and Healthy classes. The batch size variation during model training validated its impact on accuracy level of a model, with a batch size of 16 producing the best generalisation and convergence.

On the curated new dataset, Anthracnose had the best classification accuracy (89%), while the Healthy (55%) and Mosaic Virus (29%) classes demonstrated a high degree of confusion with each other. This demonstrated the difficulty of subtle variations in disease features and visual overlap in non-controlled images.

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Mobile Deployment and Evaluation

The model performance accuracy was slightly higher on Android application compared to the jupyter Notebook environment using the same 82 curated real images. The mobile application had this specific class observation during testing:

The anthracnose class achieved a 93% accuracy, Mosaic virus got 50% accuracy, healthy had 55% while downy mildew was 40%,

In comparison with the test on jupyter notebook platform, these improvement in class accuracy may be justified by the hardware configuration and the relationship between the real-world images and the training dataset or the difference in the inference mode in the form of batch size as demonstrated by Nabavinejad et al. (2021) stating that batch size and hardware specific optimisation can influence results due to varying floating point operations.

These results support the view that deployment conditions can positively affect performance for certain classes, particularly those with clearer visual traits like Anthracnose and Mosaic Virus.

Unique Class Behaviour

The superior performance of the Anthracnose class is attributed to its unique representation in the dataset. It performed better than other classes during the model evaluation and testing. This may be attributed to its unique representation in the dataset where the Anthracnose images were mostly fruits while the other classes were leaves. This distinctive visual profile eased the learning process, thereby increasing the generalisation of the Anthracnose disease class.

On Mosaic virus class, the improved classification on mobile may imply that real-world image inputs captured on the Android device may resemble some of the images used in the training data other than artificially augmented data samples.

Research Limitations

- **Real world application**: Despite the improved accuracy with test data in the mobile application, the model had difficulty in classifying diseases that share similar features such as downy mildew and healthy class which could be due to influence of camera quality and uncontrolled environmental factors.

- **Dataset Imbalance**: Some classes had a smaller number of images which led to data imbalance and underrepresentation.
- **Limited device Testing and feedback**: Due to time constraint, the model was only tested on android device with low user feedback mechanism which limits it generalisation to other low resource devices.
- **Limited Disease class**: The developed model was created with only four classes. There is need to increase the number of disease classes as well as creating an option that says if the image classified is a watermelon disease or not. Considering that the mobile app classifies any image it receives to be one of the four classes it was trained with.

Broader Implications

Application of AI tools in agriculture is supported by this research work. The potential of deploying deep learning models in resource constraint environment like agriculture validates the project purpose. The use of android device for early watermelon disease detection and classification demonstrated the ability of utilising AI tools in agriculture including small holder farmers. The research also supported that ongoing discussion of ethics in responsible AI usage and deployment where real world validation must be achieved before commercialisation of the product to reduce bias.

Additionally, the social impact is relevant. The use of mobile phones to achieve real-time and offline disease detection and classification empowers farmers to take swift action, thereby increasing yields, reducing economic losses, and minimising dependence on limited agricultural professionals.

Recommendations for Further Study

- **Data Expansion**: For future research, there should be concentration on gathering more varieties of field-based images that represent environmental condition as well as addition of new disease classes to the model to improve robustness.
- **Test on various device**: There is need for deploying and evaluating the classification model on other low resource devices and embedded platforms to enhance generalisation.
- **User feedback**: To improve model adaptation and trustworthiness, feedback mechanisms from users should be considered during design phase.

- **Multilingual and Accessible User Interface**: Inclusiveness should be considered during future designs to accommodate language barriers through language option, voice prompts and visual guides.
- **Integration with IoT and Cloud Services**: Future development should include linkage to centralised platform connected to farm IoT systems.
- **Performance Evaluation through Field Trials**: To ensure user acceptance and long-term usage of the product, field-based experiment and trial should be conducted with the intended users.

Self-Reflections and Learning outcome

This project has been an exceptional learning experience and fulfilment of the desire to develop an AI solution in agricultural field. It offered many insights and opportunities for future AI based development in food production. The model development and deployment to android device identified the relevance of combining production and performance evaluation in projects. This creates an assurance on the product and provides opportunity for improvement when human sensitivity, environmental and technical factors are considered. The research proves that a lightweight MobileNetV2 based deep learning model offers a strong foundation for building agricultural AI tools for disease classification in low resource environment provided the design and evaluation are carefully performed.

Every stage of the project helped to create an applied AI solution that has practical applications to agriculture. From model design to mobile integration phase. Despite their drawbacks, it created more knowledge and recommendation for future development. The experience also reaffirmed the importance of interdisciplinary thinking, which involves utilising design, ethics, computer science, and agriculture to develop technology that meets human needs.

Conclusion

The main aim of the research which was to create, implement, and deploy a lightweight deep learning model with MobileNetV2 architecture for the classification of watermelon diseases on Android smartphones was achieved. Despite the challenges discovered, it offered insights into the possible areas of improvement for field deployment and proved that real-time mobile inference was feasible. The study offers a replicable model development framework, establishes the foundation for future developments in precision farming solutions, and make a theoretical and practical contribution to the field of AI in agriculture.

The developed model has the potential to be a useful tool for promoting sustainable agriculture and food security for smallholder farmers at the local level with careful adjustments, rigorous testing, and practical application.

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